Artificial Intelligence and Market Manipulation:

Challenges for Market Abuse Regulations and Governance of Algorithmic Trading

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"It is a law of nature we overlook, that intellectual versatility is the compensation for change, danger, and trouble. An animal perfectly in harmony with its environment is a perfect mechanism. Nature never appeals to intelligence until habit and instinct are useless. There is no intelligence where there is no change and no need of change. Only those animals partake of intelligence that have to meet a huge variety of needs and dangers."

– H. G. Wells, *The Time Machine* (1895), Chapter 10, 78

ABSTRACT

The financial trading industry is amid a technological (r)evolution, fuelled by Artificial Intelligence (AI) and its subfield of Machine Learning (ML). As AI-based algorithmic trading systems become increasingly sophisticated, capable, and autonomous, the active role of human actors is in decline. At the same time, concerns are rising over the implications for market efficiency, integrity, and stability, mainly due to the unintended consequences and potential misuse of advanced applications. This dissertation analyses, conceptualises, and evaluates the novel risks for capital markets posed by ML and other advanced methods, focusing on (Deep) Reinforcement Learning (DRL) methods as a case study. Adopting an interdisciplinary approach, this work bridges insights from Finance, Law, and Informatics.

The dissertation begins by exploring how subsequent AI generations in financial trading have spurred greater system complexity. Drawing on state-of-the-art research in Computational Finance, it highlights how the rapid progress in ML—exemplified by DRL applications—has fundamentally impacted capital markets, including the emergence of new market abuse risks. Hence, the dissertation conceptualises four basic scenarios, categorised by varying degrees of human involvement, in which AI trading may foster market manipulation. The discussion extends to the enforcement of market conduct rules, focusing on the heightened risks introduced by DRL methods, which enable autonomous trading agents capable of engaging in market manipulation or even 'tacit' collusion, regardless of specific human intent.

Building on these insights, the dissertation evaluates the adequacy of the EU regulatory framework for algorithmic trading—specifically MiFID II/MiFIR and MAR/MAD. It explores the ethical and legal challenges arising from the key techno-methodical specificities of AI systems, including their operational 'autonomy' and 'opacity'. Through a detailed analysis of critical elements of algorithmic trading regulation—such as (i) liability rules for market abuse, (ii) enforcement regimes, (iii) supervisory frameworks, and (iv) governance of trading technology—the research identifies significant regulatory gaps and proposes a range of policy solutions. Key recommendations include (i) clarifying the legal definition of market manipulation, (ii) strengthening liability and enforcement regimes, (iii) adopting a behavioural-based approach to market conduct supervision, and (iv) establishing an EU-wide supervisory technology (SupTech) ecosystem for effective cross-market surveillance. Finally, the dissertation introduces a novel risk-based regulatory approach for AI applications in algorithmic trading, inspired by the EU AI Act. This approach departs from the prevailing principle of 'technology neutrality', emphasising proportional requirements for AI governance across the entire lifecycle from an engineering perspective.

Ultimately, this dissertation advances an interdisciplinary research agenda at the intersection of Finance, Law, and Informatics, aiming to inform and support academics, policymakers, and financial regulators in crafting future-proof regulations for AI within the domain of regulated financial trading.

DEDICATION

To my beloved parents, Cinzia and Fabio, who have always believed in me and provided unwavering support throughout the Journey. Your unconditional presence, financial assistance, and understanding in allowing me to pursue my dreams from distance have been invaluable. I am profoundly aware of the sacrifices you have made and the moments we have missed together. Your profound love and encouragement have been my guiding light.

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To all the remarkable individuals I worked with throughout my doctoral research project, I am honoured by your support, guidance, and contributions. Thank you for the invaluable knowledge and experiences gained through our collaborations.

Finally, I acknowledge the use of AI-based proofreading tools for certain parts of the manuscript. This assistance was limited to refining language and clarity and did not compromise the originality, independence, or intellectual integrity underpinning

this work. All ideas, analyses, and research activities presented are solely the product of my own efforts, abilities, and limitations.

TABLE OF CONTENTS

TABLE OF ABBREVIATIONS

ACM	Association for Computing Machinery
ABM	Agent-Based Modelling
AFM	Dutch Authority for the Financial Markets
AGI	Artificial General Intelligence
AI	Artificial Intelligence
AIaaS	Artificial Intelligence-as-a-Service
AltData	alternative data
ANN	artificial neural network
ASIFMA	Asia Securities Industry & Financial Markets Association
BaFin	German Bundesanstalt für Finanzdienstleistungsaufsicht
BIS	Bank for International Settlements
BoE	Bank of England
CAIDP	Center for AI and Digital Policy
CFR	Charter of Fundamental Rights of the European Union
CFTC	US Commodity Futures Trading Commission
CJEU	Court of Justice of the European Union
CMVM	Comissão do Mercado de Valores Mobiliários
CNN	Convolutional Neural Network
Consob	Commissione Nazionale per le Società e la Borsa
DEA	direct electronic access
DNB	De Nederlandsche Bank

DL	Deep Learning
DRL	Deep Reinforcement Learning
ESAs	European supervisory authorities
ESMA	European Securities and Markets Authority
EU	European Union
FCA	UK Financial Conduct Authority
FINRA	US Financial Industry Regulatory Authority
FinTech	financial technology
FMSB	Financial Markets Standards Board
FSB	Financial Stability Board
FSC	Taiwan's Financial Supervisory Commission
FX	foreign exchange
G7	Group of Seven
GANs	Generative Adversarial Networks
HFT	high-frequency trading
IBM	International Business Machines Corporation
ICT	Information and Communication Technologies
IEEE	The Institute of Electrical and Electronics Engineers
IMDA	Singapore's Infocomm Media Development Authority
IMF	International Monetary Fund
IOSCO	International Organization of Securities Commissions
IP	intellectual property

LIBOR	London Inter-Bank Offered Rate
LLM	large language model
MAD	European Union Market Abuse Directive
MAR	European Union Market Abuse Regulation
MAS	Monetary Authority of Singapore
MiCAR	European Union Markets in Crypto Assets Regulation
MiFID	European Union Markets in Financial Instruments Directive
MiFIR	European Union Markets in Financial Instruments Regulation
ML	Machine Learning
NCA	national competent authority
NLP	natural language processing
NYSE	New York Stock Exchange
OECD	Organisation for Economic Co-operation and Development
OSFA	one-size-fits-all
OSFI	Canada's Office of the Superintendent of Financial Institutions
OTC	over-the-counter
OTR	order-to-trade ratio
PDPC	Personal Data Protection Commission Singapore
RegTech	regulatory technology
Regulation AT	CFTC proposed Regulation Automated Trading
RL	Reinforcement Learning
RLHF	Reinforcement Learning with Human Feedback

RLHI	Reinforcement Learning with Heuristic Imperatives
RTS	regulatory technical standards
SaaS	Software-as-a-Service
SEC	US Securities and Exchange Commission
SL	Supervised Learning
STORs	suspicious transactions and order reports
SupTech	supervisory technology
TFEU	Treaty on the Functioning of the European Union
UK	United Kingdom
UL	Unsupervised Learning
US	United States
WB	World Bank
WEF	World Economic Forum
XAI	Explainable AI

Table of Statutes and Other Primary Legal Sources

I. European Union

Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments [2014] OJ L 173/349	166, 167, 168, 169, 170, 171, 177, 178, 179, 180, 181, 184, 187, 188, 210, 240, 247, 257, 279, 287, 291, 295, 297, 305, 311, 328, and 368
Regulation (EU) No 1095/2010 of the European Parliament and of the Council of 24 November 2010 establishing a European Supervisory Authority (European Securities and Markets Authority), OJ L 331/84	183 and 186
Regulation (EU) No 596/2014 of the European Parliament and of the Council of 16 April 2014 on market abuse (market abuse regulation) and repealing Directive 2003/6/EC of the European Parliament and of the Council and Commission Directives 2003/124/EC, 2003/125/EC and 2004/72/EC [2014] OJ L173/1	152, 153, 154, 156, 157, 158, 159, 160, 162, 163, 164, 166, 169, 174, 178, 181, 183, 184, 185, 186, 188, 203, 206, 209, 210, 226, 240, 241, 296, and 363
Regulation (EU) No 600/2014 of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments [2014] OJ L 173/84	166, 177, 179, 181, 182, 183, 187, 188, and 257
Regulation (EU) 2016/1011 of the European Parliament and of the Council of 8 June 2016 on Indices Used as Benchmarks in Financial Instruments and Financial Contracts or to Measure the Performance of Investment Funds and Amending Directives 2008/48/EC and 2014/17/EU and Regulation (EU) No 596/2014 [2016] OJ L 171/1	146
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II. Other jurisdictions (in chronological order)

1. INTRODUCTION

The idea that Artificial Intelligence[1] (AI) has the potential to mimic and even surpass human intelligence has long captivated the imaginations of many experts in the field.[2] This fascinating concept, partly influenced by science-fiction literature,[3] has over time permeated scientific circles,[4] as well as pervaded the wider public attention and

[1] The term 'Artificial Intelligence' was first used by John McCarthy at Dartmouth Conference in 1956, widely recognised as the seminal event marking the official beginning of AI as a scientific discipline. For an account of this significant event and its 50th anniversary ceremony, see James Moor, 'The Dartmouth College Artificial Intelligence Conference: The Next Fifty Years' (2006) 27(4) AI Magazine 87 <https://doi.org/10.1609/aimag.v27i4.1911> accessed 17 July 2024. While there is no universally accepted definition of AI, this dissertation adopts the workable definition put forth by the Organisation for Economic Co-operation and Development (OECD): "*An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy.*" OECD, 'Recommendation of the Council on Artificial Intelligence' (2022) OECD/LEGAL/0449, 7. Moreover, the term 'AI systems' is used to refer generally to "*software (and possibly also hardware) systems designed by humans … [that can perceive] their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal.*" European Commission, High-Level Expert Group on Artificial Intelligence, 'A Definition of AI: Main Capabilities and Scientific Disciplines' (18 December 2018) 7, <https://ec.europa.eu/futurium/en/system/files/ged/ai_hleg_definition_of_ai_18_december_1.pdf> accessed 17 July 2024.

[2] *See generally* Pew Research Center, 'Artificial Intelligence and the Future of Humans' (2018), <https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2018/12/PI_2018.12.10_future-of-ai_FINAL1.pdf> accessed 17 July 2024. To gain insights from critical perspectives, see Tony J Prescott, 'The AI Singularity and Runaway Human Intelligence' in Nathan F Lepora and others (eds), *Biomimetic and Biohybrid Systems. Living Machines 2013. Lecture Notes in Computer Science, vol 8064* (Springer Cham 2013) 438-440 <https://doi.org/10.1007/978-3-642-39802-5_59> accessed 17 July 2024; Luciano Floridi, 'Ultraintelligent Machines, Singularity, and Other Sci-fi Distractions about AI' (2022) Lavoro, Diritti, Europa, <https://ssrn.com/abstract=4222347> accessed 17 July 2024.

[3] Among the many works that have had a profound impact on shaping our understanding of AI and its potential future developments, prompting discussions about ethics, consciousness, and the relationship between humans and intelligent machines, a prominent place is reserved for Sci-Fi classics such as: Herbert G Wells, *The Time Machine* (William Heinemann 1895); Isaac Asimov, *I, Robot* (Gnome Press 1950); Isaac Asimov, *Foundation* (Gnome Press 1951); Arthur C Clarke, *2001: A Space Odyssey* (Hutchinson 1968); Philip K Dick, *Do Androids Dream of Electric Sheep?* (Doubleday 1968); William Gibson, *Neuromancer* (Ace 1984).

[4] *See* Christopher B Menadue and Karen D Cheer, 'Human Culture and Science Fiction: A Review of the Literature, 1980-2016' (2017) 7(3) SAGE Open 1 <https://doi.org/10.1177/2158244017723690> accessed 17 July 2024, discussing the impacts and influence of science fiction in scientific research.

interest. As a result, AI narratives have become deeply entrenched in the collective imagination, profoundly influencing the concerns and anticipations surrounding the future of AI.[5]

Ever since Alan Turing's seminal early work on computing machinery,[6] the controversial question of whether AI can truly replicate human 'intelligence' seems destined to remain unanswered.[7] At the same time, though, there is undeniable

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5 Isabella Hermann, 'Artificial Intelligence in Fiction: Between Narratives and Metaphors' (2023) 38 AI & Society 319 <https://doi.org/10.1007/s00146-021-01299-6> accessed 17 July 2024, analysing how science fiction literature has permeated public opinion regarding the risks and opportunities presented by AI.

6 One of the most cited works on the ability of machines to replicate human intelligence is 'Computing Machinery and Intelligence' by Alan Turing. Published in 1950, this seminal paper introduced the concept of the 'Turing Test', which proposed a criterion for determining a machine's ability to exhibit intelligent behaviour indistinguishable from that of a human. *See* Alan M Turing, 'Computing Machinery and Intelligence' (1950) LIX(236) Mind 433 <https://doi.org/10.1093/mind/LIX.236.433> accessed 17 July 2024. Turing's work is considered part of the foundation for the field of AI, sparking extensive philosophical and scientific discussions on the nature of human intelligence and the possibility of creating machines with comparable capabilities. For a discussion, see Camilo Miguel Signorelli, 'Can Computers Become Conscious and Overcome Humans?' (2018) 5 Frontiers in Robotics and AI, Article 121 <https://doi.org/10.3389/frobt.2018.00121> accessed 17 July 2024.

7 The complex relationship between AI and human intelligence is subject of interesting debate, showing the emergence of conflicting perspectives. *See, e.g.*, Marieke MM Peeters and others, 'Hybrid Collective Intelligence in a Human–AI Society' (2021) 36 AI & Society 217, 219-224 <https://doi.org/10.1007/s00146-020-01005-y> accessed 17 July 2024, discussing the 'technology-centric', 'human-centric', and 'collective intelligence' perspectives. It is worth, however, clarifying that 'intelligence', as we understand it in the human or animal context, is not a characteristic properly attributable to AI. The comparison between AI and human intelligence can thus be misleading. Actually, the inner workings of the human brain still remain a profound mystery, despite centuries of philosophical and scientific research. While AI has certainly demonstrated remarkable achievements in performing specific tasks that traditionally require human intelligence and even surpassed human capabilities in certain narrow domains, it lacks general human attributes, such as, for instance, cognition, consciousness, and emotional intelligence. In addition, although AI systems enjoy learning and adaptive capabilities within their specific application domains, at the end of the day they are ultimately dependent on human design and oversight. Humans play indeed a crucial role in creating, maintaining, and ensuring effective, safe, and responsible use of AI systems. *See, e.g.*, Sana Khanam, Safdar Tanweer, and Syed Khalid, 'Artificial Intelligence Surpassing Human Intelligence: Factual or Hoax' (2020) 64(12) The Computer Journal 1832, 1837-1838 <https://doi.org/10.1093/comjnl/bxz156> accessed 17 July 2024. Nonetheless, it should not be rule out altogether human ability to create artefacts that approximate human-like intelligence in the future. *See, e.g.*, François Chollet, 'On the Measure of Intelligence' (2019) arXiv preprint 1 <https://doi.org/10.48550/arXiv.1911.01547> accessed 17 July 2024. From another perspective, it is noteworthy that AI research also provides an exciting opportunity to deepen our understanding of human intelligence and consciousness, and in the future, it may help us shed light on the intricate workings of the human mind. *See, e.g.*, Xingxia Zhang and others, 'Psychological Mechanism of Language cognition to "Awaken" Artificial Intelligence' (2022) Psychological Trauma: Theory,

evidence of AI progressively outperforming humans in intricate tasks across diverse domains.[8] A defining moment in this trajectory unfolded in 1997 when *Deep Blue*, an early AI-powered chess-playing system developed by *IBM*, triumphed over reigning world chess champion Garry Kasparov.[9] This episode marked a milestone in the history of Computer Science highlighting the ability of AI to surpass humans in traditional board games. Soon after, examples of AI superiority went far beyond chess.

In 2016, *Google DeepMind*'s *AlphaGo* astounded the world by defeating the world champion Go player, Fan Hui, showcasing AI's exceptional aptitude in mastering complex board games.[10] Pushing the boundaries further, AI quickly demonstrated its supremacy in video games as well. In 2018, another *DeepMind*-developed AI system, *AlphaStar*, emerged triumphant against professional human players in *StarCraft II*, a popular real-time strategy video game known for its playing difficulty.[11] These

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Research, Practice, and Policy <https://psycnet.apa.org/doi/10.1037/tra0001305> accessed 17 July 2024.

8 For a survey study providing a comprehensive analysis of the predictions and perspectives, from experts in the field, regarding AI surpassing human performance, see Katja Grace and others, 'Viewpoint: When Will AI Exceed Human Performance? Evidence from AI Experts' (2018) 62 Journal of Artificial Intelligence Research 729 <https://www.jair.org/index.php/jair/article/view/11222/26431> accessed 17 July 2024. For a perspective on the collaboration between AI and humans to achieve enhanced capabilities and outcomes, known as 'hybrid intelligence', see Dominik Dellerman and others, 'Hybrid Intelligence' (2019) 61 Business & Information Systems Engineering 637 <https://doi.org/10.1007/s12599-019-00595-2> accessed 17 July 2024.

9 George Johnson, 'To Test a Powerful Computer, Play an Ancient Game' (*The New York Times*, 29 July 1997) <https://www.nytimes.com/1997/07/29/science/to-test-a-powerful-computer-play-an-ancient-game.html> accessed 17 July 2024. It should however be noted that Deep Blue was not AI in the strict sense. *Cf.* Deborah Yao, '25 Years Ago Today: How Deep Blue vs. Kasparov Changed AI Forever' (*AI Business*, 11 May 2022) <https://aibusiness.com/ml/25-years-ago-today-how-deep-blue-vs-kasparov-changed-ai-forever> accessed 17 July 2024; International Business Machines Corporation (IBM), 'Deep Blue' <https://www.ibm.com/ibm/history/ibm100/us/en/icons/deepblue> accessed 17 July 2024.

10 BBC, 'Google achieves AI 'breakthrough' by beating GO champion' (*BBC News*, 27 January 2016) <https://www.bbc.com/news/technology-35420579> accessed 17 July 2024.

11 Rachel Metz, 'Google's StarCraft-Playing AI Is Crushing Pro Gamers' (*CNN Business*, 24 January 2019) <https://edition.cnn.com/2019/01/24/tech/deepmind-ai-starcraft/index.html> accessed 17 July 2024.

remarkable achievements underscore the ever-evolving capabilities of AI algorithms[12], leaving no doubt about their potential to outshine humans in increasingly complex—albeit narrow—domains, transcending the realm of games.[13]

Some of the most recent AI achievements involve a particular category of Machine Learning[14] (ML)—which itself is a subfield of AI—known as 'Deep Reinforcement Learning'[15] (DRL).[16] This rapidly advancing field within ML research enables the development of 'software agents'[17] capable of learning how to achieve

[12] In the Turing sense, an 'algorithm' refers to a step-by-step procedure or set of rules that can be followed to solve a specific problem or perform a particular computation. It is a precise and unambiguous description of a sequence of operations that can be executed by a 'Turing machine', a theoretical computing device capable of simulating any algorithm. The concept of an algorithm in the Turing sense captures the fundamental idea of a systematic and mechanical approach to problem-solving in the field of computer science and mathematics. *See* Alan M Turing, 'On Computational Numbers, with an Application to the Entscheidungsproblem' (1936) s2-42(1) Proceedings of the London Mathematical Society 230 <https://doi.org/10.1112/plms/s2-42.1.230> accessed 26 November.

[13] Sebastian Risi and Mike Preuss, 'From Chess and Atari to StarCraft and Beyond: How Game AI is Driving the World of AI' (2020) 34 KI - Künstliche Intelligenz 7 <https://doi.org/10.1007/s13218-020-00647-w> accessed 17 July 2024, who describe how successes in AI applications in gaming can benefit and often influence other areas of AI research.

[14] Confusion between the terms 'Artificial Intelligence' and 'Machine Learning' is common among the public. While Machine Learning is a specific subfield within the broader domain of AI, it explores the capacity to enhance performance by leveraging experience derived from observed data. It is worth noting that while some AI systems rely on ML methods, not all AI systems adopt this approach. *See* Stuart J Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach* (4th edn, Pearson 2021) 19-20.

[15] The field of Deep Reinforcement Learning represents a cutting-edge area of ML research that has emerged through the integration of Reinforcement Learning with Deep Learning methods. A detailed explanation of these methods, along with their specific application in the context of financial trading, can be found in Chapter 2.4.B, where the reader can delve into a comprehensive discussion on the subject.

[16] For a review of the success obtained by DRL applications in various video games, see Kun Shao, Zhentao Tang, and Yuanheng Zhu, 'A Survey of Deep Reinforcement Learning in Video Games' (2019) arXiv preprint 1 <https://arxiv.org/abs/1912.10944> accessed 17 July 2024.

[17] As for the case of 'Artificial Intelligence', there is no universally accepted definition of what a 'software agent' is. However, in Agent-based Software Engineering, an 'agent' is an overarching term that encompasses various specific agent types. It refers to a software and/or hardware component that possesses the capability to perform precise actions in order to achieve tasks on behalf of its user. Hyacinth S Nwana and Divine T Ndumu, 'A Brief Introduction to Software Agent Terminology' in Nicholas R Jennings and Michael J Wooldrigde (eds), *Agent Technology: Foundations, Applications,*

predefined goals within complex environments by solving sequential decision-making problems. As will be discussed, DRL-based agents show promising results in several complex domains, including capital markets trading.[18]

Based on the remarkable success of ML methods and related applications, this dissertation aims to shed light on the potential for 'intelligent machines'[19] to outsmart human intelligence in the domain of capital markets trading. For the sake of terminology clarification, although the terms AI and ML may be used interchangeably throughout this dissertation, the term 'AI' will primarily denote systems that specifically incorporate ML methods. However, apart from the successes achieved by ML, particularly its subfield of Deep Learning (DL) methods, in highly specialised fields of AI, our focus lies on the darker aspects of AI in finance: its potential for market

and Markets (Springer Cham 1998) 29-30. For the purpose of this dissertation, we will refer to 'autonomous trading agents' and 'software agents' interchangeably.

[18] *See* discussion in Chapter 2.4.B.

[19] The notion of 'intelligent machines' finds its origins in the ground-breaking contributions of the Hungarian-American polymath John von Neumann, considered one of the fathers of computing like Alan Turing. Von Neumann's seminal work, known as the 'von Neumann machine', pioneered the notion of programmable computers capable of executing a set of instructions and evolving through learning. His visionary ideas on the architecture and organisation of computers established a foundation that continues to shape the development of today's computing systems. *See* Robert F Rosin, 'Von Neumann Machine', *Encyclopedia of Computer Science* (4th edn, 2003) 1841-1842 <https://dl.acm.org/doi/abs/10.5555/1074100.1074911> accessed 17 July 2024. For a discussion of the distinction between computers and intelligent machines, see Merrill M Flood, 'What Future Is There for Intelligent Machines?' (1963) 11(6) Audio Visual Communication Review 260 <https://link.springer.com/content/pdf/10.1007/bf02822650.pdf> accessed 17 July 2024, which highlights the relevance of von Neumann's scientific contribution to future developments in Computer Sciences.

manipulation[20] and even collusion[21] in capital markets, in novel and unprecedented ways.[22] Specifically, this dissertation seeks to investigate how increasingly 'intelligent' AI trading systems, based on (D)RL methods, may become capable of cheating in pursuit of their goals, thus facilitating market manipulation regardless of specific human intent—i.e. without being explicitly designed or instructed to do so. Considering the potential materialisation of these threats, we will thus (i) evaluate the adequacy of existing legal and regulatory frameworks in addressing such risks, (ii) identify potential shortcomings, and (iii) discuss innovative regulatory solutions for dealing with these challenges.

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[20] For the purpose of this dissertation, the term 'market manipulation' is specifically defined within the context of capital markets. It encompasses deliberate and deceptive activities undertaken by individuals or entities to distort the normal functioning of financial markets for personal gain or to create an artificial advantage. Market manipulation is widely recognised as a detrimental form of market abuse by legal systems across the globe, as it undermines market integrity and fairness, erodes investor confidence, and disrupts the efficient allocation of capital. *See* International Organization of Securities Commissions (IOSCO), 'Investigating and Prosecuting Market Manipulation' (May 2000) Report of the Technical Committee of IOSCO <http://www.iosco.org/library/pubdocs/pdf/IOSCOPD103.pdf> accessed 17 July 2024. To gain a preliminary understanding of the various forms of market manipulation, readers are referred to: Tālis J Putniņš, 'Market Manipulation: A Survey' (2011) 26(5) Journal of Economic Surveys 952 952 <https://doi.org/10.1111/j.1467-6419.2011.00692.x> accessed 17 July 2024; Tālis J Putniņš, 'An Overview of Market Manipulation' in Carol Alexander and Douglas Cumming (eds), *Corruption and Fraud in Financial Markets: Malpractice, Misconduct and Manipulation* (John Wiley & Sons 2020) 13-44.

[21] The term 'collusion' commonly denotes any form of coordination or agreement among competing firms aimed at strategic cooperation by market partitioning or competition restriction. *See* OECD, 'Glossary of Industrial Organisation Economics and Competition Law' (1993) 20-22 <https://www.oecd.org/regreform/sectors/2376087.pdf> accessed 17 July 2024. In economics, a distinction is generally made between two forms of collusion: 'explicit' and 'tacit'. The former refers to anti-competitive conduct based on an explicit agreement and mutual understanding between rival firms. The latter, in contrast, encompasses anti-competitive coordination achieved without explicit agreements. *See, e.g.*, OECD, 'Algorithms and Collusion: Competition Policy in the Digital Age' (2017) 19 <https://www.oecd.org/daf/competition/Algorithms-and-colllusion-competition-policy-in-the-digital-age.pdf> accessed 17 July 2024. However, this dissertation primary focuses on the question of whether trading algorithms and strategies can facilitate 'tacit' collusion in capital markets, despite the latter not typically manifesting structural features associated with collusion risk.

[22] For a review of the literature on the possible facets that the dark side of AI can take on in electronic markets, see Yunfei Xing, Lu Yu, and Justin Z Zhang, 'Uncovering the Dark Side of Artificial Intelligence in Electronic Markets: A Systemic Literature Review' (2023) 35(1) Journal of Organizational and End User Computing 1 <http://dx.doi.org/10.4018/JOEUC.327278> accessed 17 July 2024.

But before embarking on this research journey, this introductory chapter serves several preliminary objectives. First, we aim to set the scene by contextualising ML progress in algorithmic trading within the broader debate on AI governance[23]. This will help establish a foundation for understanding the evolving role of AI and its implications for capital markets and financial regulation (Chapter 1.1.). Second, we provide an overview of the current state of the scientific debate on algorithmic trading regulation through a concise yet essential literature review. This preliminary exercise allows us to identify emerging research gaps and situates the present dissertation within the scientific literature (Chapter 1.2). Drawing from the identified gaps, the next objective is to elucidate the rationale behind this dissertation and articulate its central

[23] With the term 'AI governance', this dissertation generally refers to the system of rules, policies, and processes established to regulate and oversee the development, deployment, and use of AI systems within an organisation. AI governance thus encompasses the techno-organisational frameworks and mechanisms designed to ensure that AI systems are developed, deployed, and used in a manner that adhere to established ethical, legal, and societal standards, and that potential risks and harms associated with AI adoption can be effectively identified, managed, and mitigated. Among other things, AI governance frameworks include guidelines, principles and rules for responsible data processing, transparency in AI decision-making processes, human accountability and liability for AI outcomes and actions, and mechanisms for addressing potential biases and discrimination in AI algorithms. *Cf.* Allan Dafoe, 'AI Governance: A Research Agenda' (Future of Humanity Institute, University of Oxford 2018) <https://www.fhi.ox.ac.uk/wp-content/uploads/GovAI-Agenda.pdf> accessed 17 July 2024; Allan Dafoe, 'AI Governance: Overview and Theoretical Lenses' in Justin B Bullock (ed) *The Oxford Handbook of AI Governance* (Oxford University Press 2022) C2S1-C2N <https://doi.org/10.1093/oxfordhb/9780197579329.013.2> accessed 17 July 2024, who examines the concept of AI governance from a theoretical perspective; Matti Mäntymäki and others, 'Defining Organizational AI Governance' (2022) 2 AI and Ethics 603 <https://doi.org/10.1007/s43681-022-00143-x> accessed 17 July 2024, who define the organisational dimensions of AI governance; Matti Mäntymäki and others, 'Putting AI Ethics into Practice: The Hourglass Model of Organizational AI Governance' (2022) arXiv preprint 1 <https://doi.org/10.48550/arXiv.2206.00335> accessed 17 July 2024, providing a framework to help organisations translating ethical AI principles into concrete AI governance practice; International Association of Privacy Professionals, 'Key Terms for AI Governance' (*IAPP.org*, November 2023) <https://iapp.org/resources/article/key-terms-for-ai-governance> accessed 17 July 2024, providing a comprehensive glossary of AI governance-related terms; *see also* Samuli Laato and others, 'AI Governance in the System Development Life Cycle: Insights on Responsible Machine Learning Engineering' in Ivica Crnkovic (ed), *CAIN '22: 1st Conference on AI Engineering - Software Engineering for AI* (ACM 2022) 113-123 <https://doi.org/10.1145/3522664.3528598> accessed 17 July 2024, highlighting the fundamental importance of addressing AI governance aspects along and within the entire AI lifecycle. Given the multiplicity and scope of the risks associated with AI adoption, there is a growing consensus among world governments to place AI governance as a priority on their policy agendas. *See, e.g.*, AI Safety Summit, 'The Bletchley Declaration by Countries Attending the AI Safety Summit, 1-2 November 2023' (1 November 2023) Policy Paper <https://www.gov.uk/government/publications/ai-safety-summit-2023-the-bletchley-declaration/the-bletchley-declaration-by-countries-attending-the-ai-safety-summit-1-2-november-2023> accessed 17 July 2024.

research questions. Additionally, we will delineate its research scope and methodology. By doing so, the aim is to provide the reader with a clear understanding of how this research fits the scientific domain and its underlying approach to addressing the identified gaps in the literature (Chapter 1.3). Subsequently, we explain how the investigation proposed by this dissertation intends to contribute to the growing body of scientific literature in AI governance and regulation in finance. This clarification not only underscores the significance of this dissertation but also highlights how the proposed research approach and methodology together contribute to expanding knowledge in the field (Chapter 1.4). Lastly, we will provide the reader with a preview of the contents of the subsequent chapters of this dissertation (Chapter 1.5).

1.1 Setting the Scene: the AI Factor in Capital Markets Trading

As a foundational technology of the digital era, AI offers the transformative potential to revolutionise our lives in profound ways, for either good or evil.[24] Among the wide-ranging benefits, AI is believed to enhance productivity, optimise resource allocation, and attain broader societal goals like social cohesion and economic sustainability.[25] Nevertheless, a growing sense of apprehension permeates the thoughts of experts and public alike, concerning the radical integration of AI into businesses, public services, and our daily lives.[26] These concerns mainly stem from the recognition that unethical

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[24] *See generally* Spyros Makridakis, 'The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms' (2017) 90 Futures 46 <https://doi.org/10.1016/j.futures.2017.03.006> accessed 17 July 2024, who highlights the parallels between the ongoing AI revolution and previous transformative periods such as the Industrial and Information revolutions, emphasising the high potential impact of AI on society; *see also* Robin Li, *Artificial Intelligence Revolution: How AI Will Change our Society, Economy, and Culture* (Skyhorse 2020).

[25] *See generally* Luciano Floridi and others, 'AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations' (2018) 28 Minds and Machines 689, 690-694 <https://link.springer.com/article/10.1007/s11023-018-9482-5> accessed 17 July 2024; *see also* Ricardo Vinuesa and others, 'The Role of Artificial Intelligence in Achieving the Sustainable Development Goals' (2020) 11 Nature Communications, Article No 233 <https://www.nature.com/articles/s41467-019-14108-y> accessed 17 July 2024, focusing on the potential advantages offered by AI to achieve sustainability goals.

[26] *See generally* Daron Acemoglu, 'Harms of AI' (2021) NBER Working Paper 29247 <https://www.nber.org/system/files/working_papers/w29247/w29247.pdf> accessed 17 July 2024.

and/or unsafe AI deployment can worsen existing societal issues, including opaque and biased decision-making, discriminatory practices, and the erosion of human rights and privacy.[27]

Despite the active involvement of public authorities in AI policy and law, it can generally be said that the observable push for widespread AI adoption is primarily market-driven.[28] This trend seems to intensify existing worries about the concentration of power and control in the hands of a few dominant corporations,[29] thereby potentially undermining democratic processes and values.[30] Recent calls from AI researchers and

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27 For a reference book on how AI-powered technologies can be misused by private organisations and the inability of markets and regulation to address the resulting threats to society, see Frank Pasquale, *The Black Box Society: The Secret Algorithms That Control Money and Information* (Harvard University Press 2015).

28 *See, e.g.*, Rene Kabalisa and Jörn Altmann, 'AI Technologies and Motives for AI Adoption by Countries and Firms: A Systematic Literature Review' in Konstantinos Tserpes and others (eds), *Economics of Grids, Clouds, Systems, and Services: 18th International Conference, GECON 2021, Virtual Event, September 21-23, 2021, Proceedings* (Springer Cham 2021) 44-45 <https://doi.org/10.1007/978-3-030-92916-9_4> accessed 17 July 2024, which provide an overview of the different motivations for firms to research and adopt AI solutions; Flavio Calvino and Luca Fontanelli, 'A Portrait of AI Adopters across Countries: Firm Characteristics, Assets' Complementarities and Productivity' (2023) OECD Science, Technology and Industry Working Papers 2023/02 <https://dx.doi.org/10.1787/0fb79bb9-en> accessed 17 July 2024, who provide an analysis of firm-level characteristics related to adoption of AI applications across countries; *see also* Zaki Khoury, 'Harnessing Artificial Intelligence for Development' (*The AI Wonk Blog*, *OECD AI Policy Observatory*, 29 July 2020) <https://oecd.ai/en/wonk/harnessing-artificial-intelligence-for-development> accessed 17 July 2024, referring to the case of developing countries; *but see* The Economist, 'The Widespread Adoption of AI by Companies Will Take a While' (*The Economist*, 29 June 2023) <https://www.economist.com/leaders/2023/06/29/the-widespread-adoption-of-ai-by-companies-will-take-a-while> accessed 17 July 2024, noting that although the race toward AI by private organisations has begun, it may take longer than generally assumed to reach widespread adoption on a large scale.

29 *See, e.g.*, Pieter Verdegem, 'Dismantling AI Capitalism: the Commons as an Alternative to the Power Concentration of Big Tech' (2022) AI & Society 1 <https://doi.org/10.1007/s00146-022-01437-8> accessed 17 July 2024, focusing on the growing, if not already excessive, powers enjoyed by large technology providers firms; Daron Acemoglu and Simon Johnson, *Power and Progress: Our 1000-Year Struggle Over Technology & Prosperity* (Public Affairs 2023), providing a comprehensive chronicle of the relationship between technological innovation and power.

30 For a discussion, from an US perspective, on the challenges democratic societies face in grappling with free market capitalism ideology, see Michael J Sandel, *Democracy's Discontent: A New Edition for Our Perilous Times* (Harvard University Press 2022). For a treatise on the rising power of private organisations *vis-á-vis* public institutions in the digital era, see Oreste Pollicino, 'Potere Digitale', *Enciclopedia del Diritto (Encyclopedia of Law)* (5th edn, 2023) 410-446

stakeholders to temporarily halt large-scale AI experiments and establish comprehensive global agreements and strategies for safe and responsible deployment serve as a notable example.[31] This call comes in response to the release of powerful AI tools like ChatGPT[32] by OpenAI, which, while owning the premise to unlock numerous economic opportunities,[33] also raises fundamental questions about the societal implications of AI, including its impact on the future of work,[34] education,[35] and media communication in the public sphere,[36] as well as other domains.[37]

<https://www.digitalmedialaws.com/wp-content/uploads/2023/07/Potere-digitale_Pollicino.pdf> accessed 17 July 2024.

31 Future of Life, 'Policymaking in the Pause: What can policymakers do *now* to combat risks from advanced AI systems?' (19 April 2023) <https://futureoflife.org/wp-content/uploads/2023/04/FLI_Policymaking_In_The_Pause.pdf> accessed 17 July 2024.

32 First released in November 2022, ChatGPT is a large language model (LLM), a Generative AI tool that has recently become popular among the public for the many potentials attributed to it. ChatGPT is a natural language processing (NLP) model that can generate human-like text. It is designed to interact with users in a conversation-like context and can handle tasks such as language translation and content creation. More information is available at: <https://openai.com/blog/chatgpt> accessed 17 July 2024.

33 *See, e.g.*, Lan Chen and others, 'The Future of ChatGPT-enabled Labor Market: A Preliminary Study' (2023) arXiv preprint 1 <https://doi.org/10.48550/arXiv.2304.09823> accessed 17 July 2024, examining some of the possible ways in which Generative AI tools, such as ChatGPT, can transform some professions and jobs in the future.

34 *See, e.g.*, Ed Felten and others, 'How will Language Modelers like ChatGPT Affect Occupation and Industries?' (2023) arXiv preprint 1 <https://doi.org/10.48550/arXiv.2303.01157> accessed 17 July 2024, providing a first systematic assessment of the potential impact of LLMs on a variety of occupations.

35 *See, e.g.*, Enkelejda Kasneci and others, 'ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education' (2023) 103 Learning and Individual Differences, Article 102274 <https://doi.org/10.1016/j.lindif.2023.102274> accessed 17 July 2024.

36 *See, e.g.*, Philipp Hacker and others, 'Regulating ChatGPT and Other Large Generative AI Models' (2023) in *FAccT '23: the 2023 ACM Conference on Fairness, Accountability, and Transparency* (ACM 2023) 1112-1113 <https://doi.org/10.1145/3593013.3594067> accessed 17 July 2024.

37 The potential of Generative AI to cause harm is primarily linked to the difficulty of ensuring the transparency of the relevant ML models and AI systems' inner workings, as well as their tendency to multiply human biases and cause so-called 'hallucinations'. *See, e.g.*, Craig S Smith, 'Hallucinations Could Blunt ChatGPT's Success: OpenAI says the problem's solvable, Yann LeCun Says we'll see' (*IEEE Spectrum*, 13 March 2023) <https://spectrum.ieee.org/ai-hallucination> accessed 17 July 2024; Emilio Ferrara, 'Should ChatGPT be Biased? Challenges and Risks of Bias in Large Language Models' (2023) arXiv preprint 1 <https://doi.org/10.48550/arXiv.2304.03738> accessed 17 July 2024.

Although AI is still in its early stages,[38] with achieving 'general AI'[39] remaining a distant prospect, there exists a common fear that if AI surpasses human cognitive capabilities, it could become uncontrollable and act against our best interests.[40] The words of world-famous scientist Stephen Hawking resonate with a sense of urgency here: "the development of full artificial intelligence could spell the end of the human race".[41] In the face of these imminent challenges, it has become imperative for society to proactively address the ethical, social, and legal implications of AI and related technologies. This task necessitates a thoughtful examination of how to establish a robust governance framework that ensures technological progress becomes an

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38 Despite the rapid advancements in AI research and practice, there appears to be a prevailing sense of overconfidence, particularly among AI researchers, regarding the realistic capabilities of AI in the near future. *See, e.g.*, Melanie Mitchell, 'Why AI is Harder Than We Think' (2021) arXiv preprint 1 <https://arxiv.org/abs/2104.12871> accessed 17 July 2024.

39 General AI, also known as Artificial General Intelligence (AGI), refers to an advanced form of AI that exhibits the ability to understand, learn, and apply knowledge across a wide range of tasks and domains akin to human intelligence. Unlike 'narrow AI', which is designed to perform specific tasks within limited domains, general AI aims to possess a level of versatility and cognitive capability that surpasses the boundaries of specialised systems. For a theoretical research study attempting to formalise the notion of 'general AI' in mathematical terms, see Ben Goertzel, 'Toward a Formal Characterization of Real-World General Intelligence' in Emanuel Kitzelmann and others (eds), *Artificial General Intelligence Proceedings of the Third Conference on Artificial General Intelligence, AGI 2010, Lugano, Switzerland, March 5-8, 2010* (Atlantis Press 2010) 74-79 <https://doi.org/10.2991/agi.2010.17> accessed 17 July 2024.

40 *See, e.g.*, Deborah G Johnson and Mario Verdicchio, 'AI Anxiety' (2017) 68(9) Journal of the Association for Information Science and Technology 2267 <https://doi.org/10.1002/asi.23867> accessed 17 July 2024, pointing out that, for the most part, these concerns are due to confusion over the concept of autonomy in AI systems and humans and an overestimation of what the technology can do without its human counterparts.

41 Rory Cellan-Jones, 'Stephen Hawking warns artificial intelligence could end mankind' (*BBC*, 2 December 2014) <https://www.bbc.com/news/technology-30290540> accessed 17 July 2024.

opportunity to promote human well-being and preserve our cherished planet.[42] For many, the time to confront and anticipate these risks is already upon us—it is now![43]

A critical area deserving our utmost attention is the fast-paced world of finance, often criticised as a significant contributor to economic instability and social inequalities.[44] Undoubtedly, the continuous advancements in financial technology, or FinTech[45], including those related to AI, have transformed the landscape of financial services, offering new possibilities for consumers (e.g., in terms of products, services, and increased competition).[46] However, these advancements also imply the potential to amplify the negative—and often systemic—impacts of finance on the economy and society.[47]

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[42] Although concrete and decisive actions have not yet been taken, there is a growing consensus among various stakeholders, including governments, that robust AI governance frameworks need to be established to ensure safe and responsible adoption. As an illustration of this multi-stakeholder consensus, for example, consider the recent 'AI Safety Summit' organised by the UK government, which was attended by experts from industry, policy, and academia. For more information visit: <https://www.aisafetysummit.gov.uk> accessed 17 July 2024.

[43] *See, e.g.*, Nate Soares and Benja Fallenstein, 'Agent Foundations for Aligning Machine Intelligence with Human Interests: A Technical Research Agenda' in Victor Callaghan and others (eds), *The Technological Singularity: Managing the Journey* (Springer Cham 2017) 122 <https://doi.org/10.1007/978-3-662-54033-6_5> accessed 17 July 2024; *see also* footnote n. 31 and accompanying text.

[44] Many researchers have tried to shed light on the shadows of the world of finance and its responsibilities in contributing negatively to the troubles of the economy and society. *See, e.g.*, Anat Admati and Martin Hellwig, *The Bankers' New Clothes: What's Wrong with Banking and What to Do about It* (Princeton University Press 2014); Michael Lewis, *Liar's Poker: Rising Through the Wreckage on Wall Street* (W. W. Norton & Company 2014); Robert Z Aliber and Charles P Kindleberger, *Manias, Panics, and Crashes: A History of Financial Crises* (Palgrave Macmillan 2015).

[45] The term 'FinTech' generally refers to "technology-enabled financial solutions". Douglas W Arner, Jànos Barberis, and Ross P Buckley, 'The Evolution of FinTech: A New Post-Crisis Paradigm?' (2015) 47(4) Georgetown Journal of International Law 1271 <https://ssrn.com/abstract=2676553> accessed 17 July 2024.

[46] *See generally* Thomas Philippon, 'The FinTech Opportunity' (2016) NBER Working Paper Series No 22476, 2 <https://www.nber.org/system/files/working_papers/w22476/w22476.pdf> accessed 17 July 2024; *see also* Maria Demertzis, Silvia Merler, and Guntram B Wolff, 'Capital Market Union and the Fintech Opportunity' (2018) 4(1) Journal of Financial Regulation 157, discussing the challenges facing EU financial regulators in seizing the opportunities presented by FinTech <https://doi.org/10.1093/jfr/fjx012> accessed 17 July 2024.

[47] *See* Ross P Buckley and others, 'The Dark Side of Financial Transformation: The New Risks of FinTech and the Rise of TechRisk' (2019) European Banking Institute Working Paper Series 2019 –

Despite the ever-growing number of AI use cases in financial services, this dissertation narrows its focus to the intersection of AI and algorithmic trading, particularly its subfield of proprietary trading[48]. The term algorithmic trading generally refers to the use of computer algorithms to automate various tasks within the financial trading cycle, either partially or fully.[49]

While algorithmic trading has elicited considerable debate and controversial opinions both within the policy arena and academia, the more specific ramification of AI in this area still remains relatively under-explored.[50] In fact, other AI application domains in the financial industry, such as payments, banking, and financial advisory, tend to attract greater attention from policymakers, regulators, academia, and the

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no. 54, 5-19 <https://ssrn.com/abstract=3478640> accessed 17 July 2024, who examine how greater reliance on innovative technology, digitalisation and datafication alter the systemic nature of risks in finance.

48 The term 'proprietary trading' refers to a financial practice where a financial institution, such as a bank, investment firm, or hedge fund, engages in trading activities using its own capital rather than client funds. Unlike traditional trading activities conducted on behalf of clients, proprietary trading involves the institution assuming the full risk and reaping the rewards of its trading decisions. This practice often relies on sophisticated trading strategies, advanced technology, and deep market knowledge to identify profitable opportunities and manage risks. For a critical account of the normative ambiguities regarding its legal definition from a US perspective, see R Rex Chatterjee, 'Dictionaries Fail: The Volcker Rule's Reliance on Definitions Renders it Ineffective and a New Solution is Needed to Adequately Regulate Proprietary Trading' (2011) 8(1) Brigham Young University International Law & Management Review 33 <https://digitalcommons.law.byu.edu/ilmr/vol8/iss1/4> accessed 17 July 2024. For the purposes of this research, the term is understood broadly to include activities (e.g., 'market making') that do not necessarily fall within its narrow definition. *See* Bank for International Settlements (BIS), Committee on the Global Financial System, 'Market-making and proprietary trading: industry trends, drivers and policy implications' (November 2014) CGFS Papers No 52, 10 <https://www.bis.org/publ/cgfs52.pdf> accessed 17 July 2024.

49 *See* Terrence Hendershott and Ryan Riordan, 'Algorithmic Trading and Information' (2009) UC Berkeley Working Paper 2 <http://faculty.haas.berkeley.edu/hender/ATInformation.pdf> accessed 17 July 2024, defining algorithmic trading as "*the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission*"; Andrei A Kirilenko and Andrew W Lo, 'Moore's Law versus Murphy's Law: Algorithmic Trading and Its Discontents' (2013) 27 Journal of Economic Perspectives 51, 52 <https://www.aeaweb.org/articles?id=10.1257/jep.27.2.51> accessed 17 July 2024, "*the use of mathematical models, computers, and telecommunications networks to automate the buying and selling of financial securities*"; Philip Treleaven, Michal Galas, and Vidhi Lalchand, 'Algorithmic Trading Review' (2013) 56(11) Communication of the ACM 76 <https://doi.org/10.1145/2500117> accessed 17 July 2024, "*any form of trading using sophisticated algorithms (programmed systems) to automate all or some part of the trade cycle*".

50 *See* Chapter 1.2.

general public, perhaps due to the fact that consumer-facing financial services have a more direct and tangible impact on individuals' daily lives.[51] In contrast, the inner workings of capital markets, particularly the realm of algorithmic trading, not only remain largely concealed from the average person's understanding, but also increasingly complex for policymakers and regulators to address.[52]

Building upon these introductory remarks, the primary objective of this dissertation is to examine the implications of AI for the safety and integrity of global capital markets. As will be discussed, thanks to AI—particularly its subfield of ML—, human experts at investment firms can today research, deploy, and utilise increasingly powerful and sophisticated trading algorithms. Innovative ML approaches not only enable to augment human traders' capabilities, leveraging synergetic human-AI system interactions,[53] but also to research artificial trading agents able to operate in markets with increasing autonomy. But since contemporary algorithmic trading systems enjoy growing operational autonomy and may, at times, function as black boxes, this raises concerns about the ability of their human stakeholders to meaningfully control them in order to prevent unintended consequences or potential misuse. In this latter regard, not only AI trading enables humans to optimise their manipulative strategies but may

[51] This observation is also reflected in emerging policy initiatives regarding the regulation of AI applications in the financial sector. For instance, the emerging EU's approach to regulating AI, which will be discussed in subsequent chapters, explicitly regulates only those AI applications that have the potential to directly harm consumers' fundamental rights, such as credit scoring, life insurance, and health insurance, health insurance. This limited scope indicates a narrower focus on addressing specific risks in certain areas, rather than comprehensively addressing the broader implications of AI.

[52] In recent years, there has been a proliferation of books aiming to shed light on the world of financial trading, thereby raising public awareness of the practices employed by sophisticated professional traders. Many of these practices have come under scrutiny as being considered highly questionable, if not outright improper. Some of the seminal works in this area include: Sebastian Mallaby, *More Money Than God: Hedge Funds and the Making of a New Elite* (Penguin 2011); Scott Patterson, *Dark Pools: The Rise of Machine Traders and the Rigging of the U.S. Stock Market* (Crown 2013); Michael Lewis, *Flash Boys: A Wall Street Revolt* (W. W. Norton & Company 2015).

[53] *See, e.g.*, Anna-Helena Mihov, Nick Firoozye, and Philip Treleaven, 'Towards Augmented Financial Intelligence' (2022) SSRN preprint 1 <https://ssrn.com/abstract=4148057> accessed 17 July 2024.

also render possible new forms of market manipulation that do not necessarily require active human involvement.

From this perspective, the integration of ML brings about a number of ethical and legal questions that urge policymakers and regulators to monitor technological developments in algorithmic trading with utmost attention. Particularly, the unsafe adoption of AI tools by investment firms can exacerbate existing 'accountability gaps' inherent in algorithmic trading, prompting important questions regarding liability for market disruption, misconduct, and resulting harm. Simultaneously, the complexity associated with AI trading and the resulting issues of control, accountability, and liability raise concerns among regulatory bodies responsible for overseeing the functioning and fairness of capital markets and the activities of regulated entities and activities.

All in all, the ongoing advances of AI in financial trading challenge the effectiveness of existing regulatory regimes on the governance of algorithmic trading as well as market abuse regulations.

1.2 Literature Review

Throughout history, technology has been a driving force behind profound transformations in the economy and society.[54] In more recent times, technological advancements have extended to the landscape of capital markets, fundamentally shaping the practices of financial negotiation and trading.[55] From the first emergence of the telegraph and telephone in the nineteenth century, enabling faster information

[54] *See, e.g.*, Acemoglu and Johnson (n 29).

[55] For a comprehensive exploration of how technological advancements have shaped the development of capital markets, leading to the occurrence of financial bubbles and instability, see Carlota Perez, *Technological Revolutions and Financial Capital: The Dynamics of Bubbles and Golden Ages* (Edward Elgar Publishing 2003).

transmission,[56] to the revolutionary impact of computers and the Internet in the twentieth century, the capital markets have experienced continuous transformation in their organisation and operation.[57] All these developments have had a lasting impact, rendering capital markets an increasingly complex, interconnected, and technology-dependent marketplace, setting the stage for further disruptive advancements in the field.[58]

As a more recent phenomenon, the rise of algorithmic trading has fuelled the beginning of a new era in capital markets in which the traditional role of human traders becomes less and less prominent. Indeed, the proliferation of sophisticated trading algorithms has given rise to high-speed trading processes and greater interconnectivity in capital markets, which, while still highly fragmented, are increasingly globalised.[59] Algorithms have become so pervasive that it now appears unfeasible to conceive capital markets operating without them.[60] According to some recent estimates, algorithmic

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56 For an in-depth investigation of the positive impacts of the telegraph and cable communication technology on market quality, see Kenneth D Garbade and William L Silber, 'Technology, Communication and the Performance of Financial Markets: 1840-1975' (1978) 33(3) The Journal of Finance 819 <https://doi.org/10.1111/j.1540-6261.1978.tb02023.x> accessed 17 July 2024.

57 For an early account on the profound changes brought about by the emergence of the Internet, see Nicholas Economides, 'The Impact of the Internet on Financial Markets' (2001) 1(1) Journal of Financial Transformation 8 <https://neconomides.stern.nyu.edu/networks/Economides_The_Impact_of_the_Internet_on_financial_markets.pdf> accessed 17 July 2024; Caitlin Zaloom, *Out of the Pits: Traders and Technology from Chicago to London* (The University of Chicago Press 2006), explaining how digital technologies, including computers and the Internet, have not only influenced marketplaces but also shaped the behaviour and professional culture of traders.

58 *See* Saule T Omarova, 'Wall Street as Community of Fate: Toward Financial Industry Self-Regulation' (2011) 150 University of Pennsylvania Law Review 411, 430 <https://scholarship.law.cornell.edu/facpub/1014> accessed 17 July 2024; Tom CW Lin, 'Compliance, Technology, and Modern Finance' (2016) 11(1) Brooklyn Journal of Corporate Finance and Commercial Law 159, 164 <https://brooklynworks.brooklaw.edu/bjcfcl/vol11/iss1/6> accessed 17 July 2024.

59 *See, e.g.*, Tom CW Lin, 'The New Financial Industry' (2014) 65(3) Alabama Law Review 566, 572-576 <https://www.law.ua.edu/resources/pubs/lrarticles/Volume%2065/Issue%203/1%20Lin%20567-623.pdf> accessed 17 July 2024; Donald MacKenzie, *Trading at the Speed of Light: How Ultrafast Algorithms are Transforming Financial Markets* (Princeton University Press 2021).

60 *E.g.*, Marc Lenglet, 'Conflicting Codes and Codings: How Algorithmic Trading is Reshaping Financial Regulation' (2011) 28 Theory, Culture & Society 44 <https://doi.org/10.1177/0263276411417444>

trading counts for the vast majority of trading activity, amounting to almost ninety percent of total trading volumes in certain asset classes.[61] With this figure in mind, it can certainly be said that market prices are almost entirely determined by interactions between algorithmic strategies, which do not always necessarily reflect our conception of prevailing general economic conditions.[62]

Not surprisingly, therefore, the phenomenon of algorithmic trading, particularly its subfield of high-frequency trading[63] (HFT), has attracted increasing interest from legal scholars, who have sought to understand its impact on market functioning and related implications for financial regulation. Despite the many advantages of algorithmic trading, there are also fundamental risks to consider, some of which are systemic in nature and go beyond those traditionally associated with human-driven

accessed 17 July 2024, arguing that the 'algorithmisation' of trading on capital markets has caused significant consequences for the nature and scope of financial regulation; Tom CW Lin, 'The New Investor' (2013) 60 UCLA Law Review 678, 687 <https://www.uclalawreview.org/pdf/60-3-3.pdf> accessed 17 July 2024, who coined the term 'cyborg finance' to describe the beginning of a new era in global finance that is increasingly dominated by trading algorithms.

61 The Economist, 'The Stockmarket Is Now Run by Computers, Algorithms and Passive Managers' (*The Economist*, 5 October 2019) <https://www.economist.com/briefing/2019/10/05/the-stockmarket-is-now-run-by-computers-algorithms-and-passive-managers> accessed 17 July 2024; European Securities and Markets Authority (ESMA), 'MiFID II Review Report: MiFID II/MiFIR review report on Algorithmic Trading' (28 September 2021) ESMA70-156-4572, 20-21, providing evidence of the growing predominance of algorithmic trading for several asset classes, including stocks, bonds, and derivatives.

62 Nicholas Megaw, 'Algorithms Prop Up Stocks as Humans Sit Out Uncertainty' (*Financial Times*, May 16, 2023) <https://www.ft.com/content/1c359259-5c29-4be6-9cb3-776dbacd0f70> accessed 17 July 2024, who discusses how algorithmic trading by hedge funds has helped support the prices of US stock indexes despite the high uncertainty in the markets due to the difficulties experienced by the banking sector during 2022 and 2023.

63 There is no universally agreed-upon definition of HFT, and different legal systems tend to treat the phenomenon in their own way. However, HFT activity share some common characteristics. These practices involve automated trading strategies that leverage advance technology and co-location to execute trades at extremely high speeds, often within milliseconds time. In addition, HFT trades are typically of limited volume, and HFT strategies are performed with no portfolio exposure remaining at the end of the trading day. *See, e.g.*, Christoph Lattemann and others, 'High Frequency Trading: Costs and Benefits in Securities Trading and its Necessity of Regulations' (2012) 4 Business & Information Systems Engineering 93, 92-94 <https://doi.org/10.1007/s12599-012-0205-9> accessed 17 July 2024.

trading.[64] To begin with, the fast and interconnected nature of trading algorithms can trigger domino effects, wherein even a single malfunction or erroneous decision in one algorithm can quickly propagate across multiple market participants, leading to market-wide disruptions.[65] Additionally, the automated nature of algorithmic trading reduces the time available for human intervention and oversight, increasing the likelihood of errors or unintended consequences that can have far-reaching implications.[66] Furthermore, the reliance on similar trading strategies or algorithms across different market participants can result in herd behaviour, wherein a common vulnerability or flaw leads to synchronised actions that exacerbate market volatility or

64 In the Finance literature, there is mixed evidence on the impact of algorithmic trading, particularly its subfield of HFT, on overall market quality. Some studies highlight the positive effects of algorithmic trading on liquidity, transaction costs, and price discovery. *See, e.g.*, Thomas Hendershott, Charles M Jones, and Albert J Menkveld, 'Does Algorithmic Trading Improve Liquidity?' (2011) 66(1) The Journal of Finance 1 <https://doi.org/10.1111/j.1540-6261.2010.01624.x> accessed 17 July 2024; Peter Gomber and others, 'High-Frequency Trading' (2011) SSRN preprint 1, 32-38, <https://ssrn.com/abstract=1858626> accessed 17 July 2024, highlighting, based on a literature review, the positive impact of algorithmic trading and HFT on market quality; Terrence Hendershott and Ryan Riordan, 'Algorithmic Trading and the Market for Liquidity' (2013) 48(4) Journal of Financial and Quantitative Analysis 1001 <https://doi.org/10.1017/S0022109013000471> accessed 17 July 2024, analysing the relationship between algorithmic trading and market liquidity; Benjamin Clapham, Martin Haferkorn, and Kai Zimmermann, 'The Impact of High-Frequency Trading on Modern Securities Markets' (2022) 65 Business & Information Systems Engineering 7 <https://doi.org/10.1007/s12599-022-00768-6> accessed 17 July 2024, arguing that investments in HFT technologies creates positive externalities to markets by reducing transaction costs and the overall quality of markets. However, other studies provide evidence of detrimental effects of certain algorithmic market practices, which seems to consume liquidity, reduce price informativeness, increase short-term volatility, posing risks of flash crashes and systemic risk. *See, e.g.*, Kirilenko and Lo (n 49); Andrei A Kirilenko and others, 'The Flash Crash: High-Frequency Trading in an Electronic Market' (2017) 72(3) The Journal of Finance 967 <https://doi.org/10.1111/jofi.12498> accessed 17 July 2024, analysing the contribution of HFT strategies in the May 6, 2010, flash crash in US markets; Brian M Weller, 'Does Algorithmic Trading Reduce Information Acquisition?' (2017) 31(6) The Review of Financial Studies 2184 <https://doi.org/10.1093/rfs/hhx137> accessed 17 July 2024, finding evidence that algorithmic trading while contributing to price discovery may nevertheless reduce price informativeness. In sum, these contrasting findings reflect the complex and nuanced relationship between algorithmic trading and market quality.

65 *E.g.*, Yesha Yadav, 'The Failure of Liability in Modern Markets' (2016) 102(4) Virginia Law Review 1031, 1071 <https://www.virginialawreview.org/wp-content/uploads/2020/12/Yadav_Online.pdf> accessed 17 July 2024; Gaia Balp and Giovanni Strampelli, 'Preserving Capital Markets Efficiency in the High-Frequency Trading Era' (2018) 2018(2) University of Illinois Journal of Law, Technology & Policy 349, 358 <https://ssrn.com/abstract=3097723> accessed 17 July 2024.

66 *E.g.*, Yadav Yesha, 'How Algorithmic Trading Undermines Efficiency in Capital Markets' (2015) 68(6) Vanderbilt Law Review 1607, 1651-1652 <https://scholarship.law.vanderbilt.edu/vlr/vol68/iss6/3> accessed 17 July 2024; Balp and Strampelli (n 65) 360.

instability.[67] Finally, the opacity of algorithmic systems, particularly those operated by the proprietary trading industry, further complicates risk assessment and regulatory oversight, posing challenges in identifying and addressing potential risks in an effective and timely manner.[68]

In addition to these overarching concerns for financial stability, a growing number of scholars have highlighted the emergence of more specific risks to market integrity[69]. In fact, algorithmic trading, and HFT in particular, has opened up to new possibilities of market abuse.[70] The existing body of literature in this area can be

[67] *E.g.*, Balp and Strampelli (n 66) 360; William Magnuson, 'Regulating Fintech' (2018) 71(4) Vanderbilt Law Review 1167, 1202 <https://scholarship.law.vanderbilt.edu/vlr/vol71/iss4/2> accessed 17 July 2024.

[68] *See, e.g.*, Yadav (n 66) 1651; *see also* Kristin N Johnson, 'Regulating Innovation: High Frequency Trading in Dark Pools' (2017) 42(4) The Journal of Corporation Law 833 <https://jcl.law.uiowa.edu/sites/jcl.law.uiowa.edu/files/2021-08/Johnson_Final_Web.pdf> accessed 17 July 2024, who instead discusses regulatory issues due to the opacity in algorithmic trading associated with certain strategies executed in dark pool venues, which are not subject to the same transparency requirements applicable to regulated markets.

[69] For a discussion on the what the goal of market integrity entails for financial regulators, as well as the ambiguities inherent in such a mandate, see Janet Austin, 'What Exactly is Market Integrity? An Analysis of One of the Core Objectives of Securities Regulation' (2017) 8(2) William & Mary Business Law Review 215 <https://scholarship.law.wm.edu/wmblr/vol8/iss2/2> accessed 17 July 2024.

[70] There is a growing body of legal literature examining how algorithmic trading, due to the corresponding increasing technological sophistication and trading strategies, has introduced new risks to market integrity, including novel forms of market manipulation. Some of the most influential studies include: Tara Bhupathi, 'Technology's Latest Market Manipulator-High Frequency Trading: The Strategies, Tools, Risks, and Responses' (2009) 11(2) North Carolina Journal of Law & Technology 377 <http://scholarship.law.unc.edu/ncjolt/vol11/iss2/7> accessed 17 July 2024; Matt Prewitt, 'High-Frequency Trading: Should Regulators Do More?' (2012) 19(1) Michigan Telecommunications and Technology Law Review 131 <https://repository.law.umich.edu/mttlr/vol19/iss1/4> accessed 17 July 2024; Frank Pasquale, 'Law's Acceleration of Finance: Redefining the Problem of High-Frequency Trading' (2015) 36 Cardozo Law Review 2085 <http://cardozolawreview.com/wp-content/uploads/2018/08/PASQUALE.36.6.pdf> accessed 17 July 2024; Gregory Scopino, 'The (Questionable) Legality of High-Speed "Pinging" and "Front Running" in the Futures Markets' (2015) 47 Connecticut Law Review 607 <https://ssrn.com/abstract=2432359> accessed 17 July 2024; Yadav (n 65); Steven McNamara, 'The Law and Ethics of High-Frequency Trading' (2016) 17(1) Minnesota Journal of Law, Science & Technology 71 <https://scholarship.law.umn.edu/mjlst/vol17/iss1/2> accessed 17 July 2024; Tom CW Lin, 'The New Market Manipulation' (2017) 66(6) Emory Law Journal 1253 <https://scholarlycommons.law.emory.edu/elj/vol66/iss6/1> accessed 17 July 2024; Merritt B Fox, Lawrence R Glosten, and Gabriel V Rauterberg, 'Stock Market Manipulation and Its Regulation' (2018) 35(1) Yale Journal on Regulation 67 <https://openyls.law.yale.edu/handle/20.500.13051/8260> accessed 17 July 2024; Tilen Čuk and Arnaud Van Waeyenberge, 'European Legal Framework for Algorithmic and High Frequency Trading (Mifid 2 and MAR): A Global Approach to Managing the Risks of the Modern Trading Paradigm' (2018)

categorised based on its primary focus and research perspective, leading to the identification of four main lines of inquiry. These include: (*i*) the examination of how algorithmic trading introduces new risks of market manipulation; (*ii*) the analysis of the limitations in applying established liability concepts to address market manipulation; (*iii*) the identification of weaknesses in the oversight of market conduct rules; and (*iv*) the evaluation of the adequacy of current regulatory frameworks in ensuring effective governance of trading technology by market participants.

First, algorithmic trading not only facilitates traditional forms of market manipulation but also introduces novel strategies spurred by advanced technological capabilities and the exploitation of specific market structures.[71] These novel manipulative practices exploit advantages such as access to information about other market participants' trading strategies (such as 'front-running'), deceptive tactics (like 'spoofing'), speed advantages, and vulnerabilities in market structure (such as 'latency arbitrage'),[72] or a combination thereof. The detrimental impact of these strategies on social welfare is widely recognised,[73] leading to their prohibition in multiple

9(1) European Journal of Risk Regulation 146 <https://doi.org/10.1017/err.2018.3> accessed 17 July 2024.

[71] *See, e.g.*, Lin (n 70) 1287-1294, who has coined the term "cybernetic market manipulation" to describe both old and new forms market manipulation strategies by means of trading algorithms; *see also* Gregory Scopino, 'Do Automated Trading Systems Dream of Manipulating the Price of Futures Contracts Policing Markets for Improper Trading Practices by Algorithmic Robots' (2015) 67(1) Florida Law Review 220, 222-234 <https://scholarship.law.ufl.edu/flr/vol67/iss1/5> accessed 17 July 2024; Gina-Gail S Fletcher, 'Legitimate yet Manipulative: The Conundrum of Open-Market Manipulation' (2018) 68 Duke Law Journal 479, 530-535 <https://scholarship.law.duke.edu/dlj/vol68/iss3/2> accessed 17 July 2024; Gideon Mark, 'Spoofing and Layering' (2019) 45(2) The Journal of Corporation Law 101, 104-108 <https://jcl.law.uiowa.edu/sites/jcl.law.uiowa.edu/files/2021-08/Mark_Final_Web.pdf> accessed 17 July 2024; Merritt B Fox, Lawrence R Glosten, and Sue S Guan, 'Spoofing and Its Regulation' (2021) 2021(3) Columbia Business Law Review 1244, 1247-1255 <https://scholarship.law.columbia.edu/faculty_scholarship/3170> accessed 17 July 2024.

[72] *See generally* Rena S Miller and Gary Shorter, 'High Frequency Trading: Overview of Recent Developments' (2016) Congressional Research Service Report, R44443, 3-6 <https://sgp.fas.org/crs/misc/R44443.pdf> accessed 17 July 2024.

[73] *See* Fox, Glosten, and Rauterberg (n 70).

jurisdictions.[74] However, the rapid evolution of market manipulation strategies presents an ongoing challenge for the law to keep pace and update regulations effectively.[75]

Second, algorithmic trading raises concerns about the application of existing prohibitions on market manipulation. Established liability rules, which rely on concepts such as intent and negligence, are ill-suited to address the unique characteristics of algorithmic trading, including its speed, autonomy, interconnectedness, and opacity.[76] Scholars have highlighted the need for a reconsideration of these rules, as they may become ineffective in addressing cases of market manipulation involving sophisticated algorithmic trading technology, especially when powered by AI.[77]

Third, the extensive market access that algorithmic trading—especially HFT—can enjoy also poses challenges to the effective supervision of market conduct rules by competent authorities.[78] The sophisticated trading strategies employed by algorithmic

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[74] For a comparative research study of the US, EU, and UK legal regimes on the fights against market manipulation and their respective enforcement challenges, see Ester Herlin-Karnell and Nicholas Ryder, *Market Manipulation and Insider Trading: Regulatory Challenges in the United States of America, the European Union and the United Kingdom* (Hart Publishing 2019).

[75] *E.g.*, Yadav (n 66) 1670-71; Lin (n 70) 1300-1303; Gina-Gail S Fletcher, 'Deterring Algorithmic Manipulation' (2021) 74(2) Vanderbilt Law Review 259, 280 and 286-291 <https://scholarship.law.vanderbilt.edu/vlr/vol74/iss2/2> accessed 17 July 2024.

[76] Issues relating to the applicability of liability rules for market misconduct involving algorithmic trading have been largely addressed by the legal scholarship. For some of the most significant accounts, see Shaun D Ledgerwood and Paul Carpenter, 'A Framework for Analyzing Market Manipulation' (2012) 8(1) Review of Law & Economics 253, 253-257 <https://doi.org/10.1515/1555-5879.1577> accessed 17 July 2024; Scopino (n 70) 648-654, who discusses some recent developments on the legal treatment of spoofing by US regulators and courts; Yadav (n 65); Lin (n 70) 1300-1303; Scopino (n 71) 258-293; Yavar Bathaee, 'The Artificial Intelligence Black Box and the Failure of Intent and Causation' (2019) 31 Harvard Journal of Law & Technology 889, 908-911 <https://jolt.law.harvard.edu/assets/articlePDFs/v31/The-Artificial-Intelligence-Black-Box-and-the-Failure-of-Intent-and-Causation-Yavar-Bathaee.pdf> accessed 17 July 2024.

[77] *See, e.g.*, Yadav (n 65); Bathaee (n 76); Fletcher (n 75).

[78] *See, e.g.*, Yesha Yadav, 'Oversight Failure in Securities Markets' (2019) 104(7) Cornell Law Review 1799 <https://scholarship.law.cornell.edu/clr/vol104/iss7/4> accessed 17 July 2024; Johannes Karremans and Magnus G Schoeller, 'MiFID II between European Rule-Making and National Market Surveillance: The Case of High-Frequency Trading' in Adrienne Héritier and Magnus G Schoeller (eds),

traders can span across different assets, markets, and borders, making it difficult for authorities to maintain oversight.[79] Some scholars argue that relying solely on trading venues as watchdogs for policing market conduct can limit supervisory effectiveness due to various factors. These include misaligned incentives resulting from competitive pressures, information and coordination costs, underinvestment in oversight technology, and a focus limited to their own markets (i.e. single-market surveillance).[80] Moreover, some scholars express concerns about the insufficient resources, tools, and authority available to financial regulators for conducting effective market surveillance.[81] Proposed solutions include equipping competent authorities with appropriate 'supervisory technology'—also known as SupTech—, increasing the recruitment and retention of experts, promoting greater standardisation and access to trading data,[82] and enhancing information sharing and coordination efforts among various supervisory bodies for cross-market and cross-border cases.[83]

As a fourth line of inquiry, researchers have critically evaluated the effectiveness of existing regulatory frameworks for the governance of algorithmic trading. The rapid innovation of trading technology, thanks to remarkable advancements in AI/ML, has

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Governing Finance in Europe: A Centralisation of Rulemaking? (Edward Elgar Publishing 2020) 32-51 <https://doi.org/10.4337/9781839101120.00009> accessed 17 July 2024.

79 *E.g.*, Janet Austin, 'Protecting Market Integrity in an Era of Fragmentation and Cross-Border Trading' (2015) 46(1) Ottawa Law Review 25, 30-38 <https://commonlaw.uottawa.ca/sites/commonlaw.uottawa.ca.ottawa-law-review/files/46-1-austin.pdf> accessed 17 July 2024.

80 *E.g.*, Yadav (n 78) 1841-1857; *see also* Janet Austin, 'Unusual Trade or Market Manipulation? How Market Abuse is Detected by Securities Regulators, Trading Venues and Self-Regulatory Organisations' (2015) 1(2) Journal of Financial Regulation 263, 274-279 <https://doi.org/10.1093/jfr/fjv003> accessed 17 July 2024.

81 *E.g.*, Austin (n 79) 58-61; Lin (n 70) 1294-1300; Fletcher (n 75) 322.

82 *E.g.*, Austin (n 78) 58-61; Hannah Harris, 'Artificial Intelligence and Policing of Financial Crime: A Legal Analysis of the State of the Field' in Doron Goldbarsht and Louis de Koker (eds), *Financial Technology and the Law: Combating Financial Crime* (Springer Cham 2022) 296-297 <https://doi.org/10.1007/978-3-030-88036-1_12> accessed 17 July 2024.

83 *E.g.*, Austin (n 78) 58-61; Austin (n 80); Yadav (n 78) 1848-1850.

raised concerns about the ability of current regulatory regimes to keep pace.[84] One area of intense research focus concerns technology-related and organisational requirements imposed on investment firms engaged in algorithmic trading.[85] For instance, there is a growing recognition of the limitations of current testing regimes in ensuring operational functionality and reliability as well as regulatory compliance.[86] Disclosure and internal risk control systems have also been subject to scrutiny and criticism,[87] particularly in the context of ML-powered trading.[88]

Another prominent area of investigation involves the effectiveness of market microstructure regulation, including mechanisms like 'circuit-breakers', in maintaining fair and orderly market conditions.[89] However, the actual effectiveness of circuit breakers is still not entirely clear, as this may be constrained by challenges in

84 Some authors argue that existing legal regimes may also fail to account for the risks associated with less sophisticated, hence non-ML trading algorithms. *See* Clara Martins Pereira, 'Unregulated Algorithmic Trading: Testing the Boundaries of the European Union Algorithmic Trading Regime' (2020) 6(2) Journal of Financial Regulation 270 <https://doi.org/10.1093/jfr/fjaa008> accessed 17 July 2024.

85 *See generally* Danny Busch, 'MiFID II: Regulating High Frequency Trading, Other Forms of Algorithmic Trading and Direct Electronic Market Access' (2016) 10(2) Law and Financial Markets Review 72 <https://doi.org/10.1080/17521440.2016.1200333> accessed 17 July 2024; Joseph Lee and Lukas Schu, 'Regulation of Algorithmic Trading: Frameworks or Human supervision and Direct Market Interventions' (2022) 33(2) European Business Law Review 193 <https://doi.org/10.54648/eulr2022006> accessed 17 July 2024.

86 *See, e.g.*, Patrick Raschner, 'Algorithms put to test: Control of algorithms in securities trading through mandatory market simulations?' (2021) European Banking Institute Working Paper Series 2021 – no. 87 <https://ssrn.com/abstract=3807935> accessed 17 July 2024

87 *See generally* Trude Myklebust, 'High-Frequency Trading: Regulatory and Supervisory Challenges in the Pursuit of Orderly Markets' in Iris Chiu and Gudula Deipenbrock (eds), *Routledge Handbook of Financial Technology and Law* (Routledge 2021) 381-403, commenting on the EU approach to the regulation of HFT.

88 *See, e.g.*, Patrick Raschner, 'Supervisory Oversight of the Use of AI and ML by Financial Market Participants' in Lukas Böffel and Jonas Schürger (eds), *Digitalisation, Sustainability, and the Banking and Capital Markets Union: Thoughts on Current Issues of EU Financial Regulation* (Palgrave Macmillan 2023) 114-121 <https://doi.org/10.1007/978-3-031-17077-5_3> accessed 17 July 2024, discussing disclosure requirements applicable to ML trading algorithms.

89 *See, e.g.*, Carsten Gerner-Beuerle, 'Algorithmic Trading and the Limits of Securities Regulation' in Emilios Avgouleas and Heikki Marjosola (eds), *Digital Finance in Europe: Law, Regulation, and Governance* (De Gruyter 2022) 125-137 <https://doi.org/10.1515/9783110749472-005> accessed 17 July 2024.

setting thresholds, balancing stability and liquidity, and adapting to the operation of complex contemporary markets.[90] Furthermore, some proposals advocate reforms to market microstructure, including the shift from existing continuous trading arrangements to batch auction methods, especially to counter many of the risks associated with HFT.[91]

For the sake of completeness, there is also a residual category that deserves at least a mention. There is a perspective held by some scholars who assert that, despite the challenges posed by algorithmic trading, regulatory efforts have demonstrated successful in mitigating risks associated with automated technology and will continue to do so in the future.[92] These proponents highlight the comprehensive approach taken by regulators, including the implementation of robust risk management practices and the continuous monitoring and adaptation of regulations to address emerging concerns. They argue that the lessons learned from regulating algorithmic trading can serve as a valuable guide for regulators grappling with the regulatory implications of advanced technologies in various other domains.[93]

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[90] *See, e.g.*, Steffen Kern and Giuseppe Loiacono, 'High Frequency Trading and Circuit Breakers in the EU: Recent Findings and Regulatory Activities' in Walter Mattli (ed), *Global Algorithmic Capital Markets: High Frequency Trading, Dark Pools, and Regulatory Challenges* (Oxford University Press 2018) 308-331 <https://doi.org/10.1093/oso/9780198829461.003.0012> accessed 17 July 2024.

[91] The design of market operations as batch auctions is believed to overcome several shortcomings of continuous trading of limit orders, see Eric Budish, Peter Cramton, and John Shim, 'The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response' (2015) 130(4) The Quarterly Journal of Economics 1547 <https://doi.org/10.1093/qje/qjv027> accessed 17 July 2024.

[92] Gerald Spindler, 'Control of Algorithms in Financial Markets: The Example of High-Frequency Trading' in Martin Ebers and Susana Navas (eds), *Algorithms and Law* (Cambridge University Press 2020) 207-220 <https://doi.org/10.1017/9781108347846.008> accessed 17 July 2024; Maria José Schmidt-Kessen, Helen Eenmaa, and Maya Mitre, 'Machines that make and keep promises – Lessons for contract automation from algorithmic trading on financial markets' (2022) 46 Computer Law & Security Review, Article No. 105717 <https://doi.org/10.1016/j.clsr.2022.105717> accessed 17 July 2024.

[93] Ibid.

In sum, while the expanding scholarship has been providing valuable insights for regulators, unresolved issues yet persist, necessitating ongoing debate and further research. Indeed, as AI advancements continue to shape this landscape, existing legal and regulatory frameworks seem to face additional limitations in addressing the corresponding technology-related risks. As a result, there emerges a need for a conceptual re-evaluation of financial regulation, including its basic assumptions and prevailing tools. It has become crucial for the field of law and regulation to adapt and innovate, recognising the importance of effective AI governance, in order to maintain its effectiveness and relevance.[94]

While interesting policy proposals are emerging, for some scholars caution is advised to prevent excessive or counterproductive regulation that may negatively impact market quality and liquidity.[95] In this sense, it is worth noting that financial regulation may always face the risks to result in regulatory complexity and disproportioned compliance costs.[96] The regulation of FinTech, including ML-powered algorithmic trading, involves an optimisation problem among conflicting regulatory goals, or the so-called 'FinTech regulation trilemma'.[97]

94 *See, e.g.*, Gina-Gail S Fletcher and Michelle M Le, 'The Future of AI Accountability in the Financial Markets' (2022) 24(2) Vanderbilt Journal of Entertainment & Technology Law 289, 304-307 <https://scholarship.law.vanderbilt.edu/jetlaw/vol24/iss2/3> accessed 17 July 2024; Robin Feldman and Kara Stein, 'AI Governance in the Financial Industry' (2022) 27(1) Stanford Journal of Law, Business & Finance 94 <https://repository.uclawsf.edu/faculty_scholarship/1867> accessed 17 July 2024.

95 *E.g.*, Carsten Gerner-Beuerle and Lukas Zierahn, 'Overreacting Algorithms in Financial Markets' (2022) SSRN preprint 1, 13-24 <https://ssrn.com/abstract=4057171> accessed 17 July 2024.

96 Peter Yeoh, 'MiFID II Key Concerns' (2019) 27(1) Journal of Financial Regulation and Compliance 110, 113-118 <https://doi.org/10.1108/JFRC-04-2018-0062> accessed 17 July 2024, who examines the impact of MiFID II implementation on the regulatory compliance activities of UK financial firms.

97 According to Professor Yesha Yadav and Professor Chris Brummer, the regulation of financial innovation entails a difficult trilemma for regulators: ensuring regulatory simplicity, maintaining market integrity, while also striving to promote innovation. *See* Chris Brummer and Yesha Yadav, 'Fintech and the Innovation Trilemma' (2019) 107 Georgetown Law Journal 235 <https://www.law.georgetown.edu/georgetown-law-journal/wp-content/uploads/sites/26/2019/02/1Fintech-and-the-Innovation-Trilemma.pdf> accessed 17 July 2024.

Against this backdrop, it is only recently that legal scholars have begun to explore the topic of AI from a more technical perspective. But at the best they have barely scratched the tip of the iceberg of the relationship between the risks to markets associated with specific ML methods and corresponding regulatory challenges.[98] There is indeed a general tendency to treat the field of ML "as a monolith and an abstraction".[99] As rightly pointed out in the literature, this attitude leaves underexplored several—perhaps most significant—harms and corresponding policy solutions associated with automated decision-making systems.[100] Under this perspective, this dissertation aims to bridge the gap in the literature by examining the legal and regulatory challenges arising from the integration of AI, particularly ML, in algorithmic trading.

As we will argue, the integration of specific ML methods into financial trading brings with it the emergence of new risks of market abuse. These applications, which operations are characterised by automation and opacity, pose challenges to the effectiveness of established regulatory frameworks governing market conduct. Moreover, the growing sophistication of trading strategies, thanks to ML, puts a strain on existing market conduct supervision systems. All this, at the same time, leads us to

98 Among these preliminary studies it is worth mentioning, for instance: Bathaee (n 70); Armin Beverungen, 'Algorithmic Trading, Artificial Intelligence and the Politics of Cognition' in Andreas Sudmann (ed), *The Democratization of Artificial Intelligence in the Era of Learning Algorithms* (transcript 2019) 77-93 <https://doi.org/10.25969/mediarep/13550> accessed 17 July 2024; Rabeea Sadaf and others, 'Algorithmic Trading, High-frequency Trading: Implications for MiFID II and Market Abuse Regulation (MAR) in the EU' (2021) SSRN preprint 1 <https://ssrn.com/abstract=3846814> accessed 17 July 2024; Fletcher (n 75); Fletcher and Le (n 94); Robert Seyfert, 'Algorithms as Regulatory Objects' (2022) 25(11) Information, Communication & Society 1542 <https://doi.org/10.1080/1369118X.2021.1874035> accessed 17 July 2024; Lee and Schu (n 85); Annunziata Filippo, *Artificial Intelligence and Market Abuse Legislation: A European Perspective* (Edward Elgar Publishing 2023).

99 David Lehr and Paul Ohm, 'Playing with the Data: What Legal Scholars Should Learn About Machine Learning' (2017) 51 University of California, Davis, Law Review 653, 655 <https://lawreview.law.ucdavis.edu/archives/51/2/playing-data-what-legal-scholars-should-learn-about-machine-learning> accessed 17 July 2024.

100 Ibid.

reflect on the adequacy of current regulatory regimes for the governance of algorithmic trading in the context of ML-powered financial trading.

1.3 Research Questions, Methodology, and Scope

In response to the gaps identified in existing legal scholarship, this dissertation addresses the following research questions:

(i) In what ways is innovation in AI, particularly in ML methods, applied to financial trading likely to introduce new risks to markets?

(ii) Is it possible that AI trading systems can develop, through ML, the ability to circumvent market rules in the context of their own autonomous conduct in pursuit of predetermined objectives?

(iii) Are current legal and regulatory regimes able to effectively address the new risks to market integrity introduced by AI trading?

(iv) What difficulties are encountered in enforcing market conduct rules against AI trading systems due to ML?

(v) In light of the growing capabilities of algorithmic trading due to ML, are current supervisory frameworks, including market surveillance mechanisms, able to cope with increasingly sophisticated manipulative strategies?

(vi) More generally, considering innovation in ML, is the current regulatory approach for the governance of algorithmic trading adequate to mitigate all the risks associated with it? In other words, does it suffice to ensure safe and responsible AI adoption?

By addressing these research questions, this dissertation aims to provide valuable insights into:

1. the implications of AI adoption in financial trading for market integrity,
2. the adequacy of existing regulatory regimes in mitigating the risks associated with AI trading,
3. the difficulties inherent in enforcing market conduct rules in the face of AI-powered trading,
4. the effectiveness of current supervisory frameworks of market conduct, and
5. the need for innovative regulatory approaches to ensure technology governance in algorithmic trading.

More generally, this dissertation seeks to advance the scientific knowledge on the interplay between AI, market manipulation, and financial regulation from an interdisciplinary perspective.

The research methodology employed in this dissertation embraces an interdisciplinary approach. This dissertation extensively draws on the triangulation[101] of theories and perspectives from diverse scientific disciplines, including Computational Finance, Computational Economics and Antitrust, Financial Law and Regulation, Law and Economics, and Law and Technology. By doing so, we aim to shed light on the risks posed by ML-based trading, with a specific focus on agents based on

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[101] The term 'triangulation' has historical origins in the field of Navigation. It is based on the idea of using the angles of two known points in the space to determine the position of an unknown third point. Phil Turner and Susan Turner, 'Triangulation in Practice' (2009) 13 Virtual Reality 171 <https://doi.org/10.1007/s10055-009-0117-2> accessed 17 July 2024. In Social Sciences research, the term 'triangulation' refers to the observation of a particular given issue from at least two different angles. Thus, it entails the approaching the study of a phenomenon with multiple perspectives and hypothesis in mind. *See* Uwe Flick, 'Triangulation in Qualitative Research' in Uwe Flick, Ernst von Kardforff, and Ines Steinke (eds), *A Companion to Qualitative Research* (SAGE Publications 2004) 178-183.

DRL methods, and their impact on market integrity. This interdisciplinary approach allows for a comprehensive understanding of the subject matter, enabling a nuanced exploration of the intricate relationship between ML, financial markets, and regulatory frameworks.

The scope of this dissertation is delineated by three main aspects. First, the research focuses on the legal and regulatory regime within the European Union (EU), however making due reference to other legal frameworks whenever a comparative analysis will be relevant. This jurisdictional scope allows for a comprehensive examination of the EU's specific legal and regulatory challenges in relation to AI trading, without compromising the global relevance of this research.

Second, this dissertation primarily centres on DRL as the foundational ML approach for artificial trading agents. While acknowledging the relevance of other ML methods—such as generative adversarial networks, transformer architectures, and federated learning in capital markets trading—, our investigation places particular emphasis on DRL due to its significance within state-of-the-art research in Computational Finance and corresponding implications for financial regulation. Moreover, the focus on DRL also allows to draw connection with other scientific disciplines—mainly, Computational Economics, Computational Finance, and Antitrust Law—interested in the understanding of artificial agent's behaviour in real life applications.

Lastly, this dissertation lives up under several key assumptions regarding the fundamental role of regulation in ensuring effective AI governance in finance. First, it recognised the essential contribution of regulation to technology governance, even in the absence of evident market failures, due to the rapid evolution of AI technology and the intrinsic high risks in capital markets. Second, it underscores the need for a dual approach to effective AI governance—one that acknowledge both the private interests of market participants and the indispensable role of public authorities in representing the public interest. From a normative perspective, indeed, preserving the public interest within a democratic system demands the participation and oversight of democratically elected bodies. Balancing market interests with public welfare is a complex challenge that necessitates market-oriented solutions integrating the public interest perspective. Therefore, AI regulation and governance should foster a collaborative approach between regulators and regulated entities. Finally, this dissertation advocates for a risk-based regulatory approach, as also outlined in the EU AI Act.[102] As we will demonstrate in the present work, risk-based regulation offers the most appropriate approach to address the risks to markets, hence to society, posed by AI applications in financial trading.

1.4 Contribution to the Literature (and beyond)

This dissertation attempts an original and significant contribution to the scientific literature by presenting an analytical framework that foster our understanding of the complex dynamics between ML-powered algorithmic trading, market manipulation, and financial regulation. It offers a fresh perspective on these increasingly interconnected areas, highlighting the need for a critical examination of existing governance and regulatory practices in the context of financial trading that is informed by an adequate understanding of ML-related technology.

As such, the findings of this dissertation not only advance knowledge within the scientific literature but also have the potential to expand the regulatory science and

[102] *See* Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 Laying Down Harmonised Rules on Artificial Intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) [2024] OJ L 1/144 [hereinafter AI Act], recitals (26) and (27). Since the official proposal of the AI Act by the European Commission on 21 April 2021, the text underwent an extensive negotiation process among EU institutions and Member States to address evolving challenges and opportunities in AI governance. A collection of key AI Act-related documents is available at: <https://www.kaizenner.eu/post/aiact-part3> accessed 17 July 2024. This collection is maintained by Kai Zenner, Head of Office for MEP Axel Voss. After more than three years of political debate and revisions, the AI Act was formally adopted by the European Council on 21 May 2024 and officially published in the OJ in July 2024. Notably, the final text introduces several adjustments compared to the original 2021 proposal, though it appears that the regulation does not introduce specific implications for AI systems used in financial trading at this stage.

practice available to policymakers and financial regulators. This is evidenced by the recognition and utilisation of the author's previous published work[103], which serves as the foundation of this dissertation, by a number of regulatory bodies such as the Portuguese financial regulator, the *Comissao do Mercado de Valores Mobiliários* (CMVM), which published a reprint version of one of the four paper on which this dissertation is based;[104] the *Dutch Authority for the Financial Markets* (AFM), for citing the same article as reference material of the risks to market integrity associated with DRL-based trading strategies;[105] and the Italian capital markets regulator, the *Commissione Nazionale per le Società e la Borsa* (Consob), for quoting previous work in its recent report on AI and market abuse regulation.[106] Moreover, the foundational work of this dissertation has been cited in reports by global private standards-setters such as the Financial Markets Standards Board (FMSB),[107] further demonstrating its impact and timely relevance.

By undertaking this dissertation research, the author's primary aspiration is to contribute to the understanding of the complex interplay between AI and capital markets trading, shedding light on the implications, challenges, and potential solutions

103 *See* 'Annex I: Publications List' at the end of the present monograph.

104 Alessio Azzutti, Wolf-Georg Ringe, and H Siegfried Stiehl, 'Machine Learning, Market Manipulation and Collusion on Capital Markets: Why the 'Black Box' Matters' (2022) Cadernos do Mercado de Valores Mobiliários, N. 71, Volume II 94, <https://www.cmvm.pt/pt/EstatisticasEstudosEPublicacoes/CadernosDoMercadoDeValoresMobiliarios/Documents/CMVM-CADERNOS-n%C2%BA71_Volume_II-07.09.2022.pdf> accessed 17 July 2024.

105 Dutch Authority for the Financial Markets (AFM), 'Machine Learning in Trading Algorithms: Application by Dutch Proprietary Trading Firms and Possible Risks' (28 September 2023) 21 <https://www.afm.nl/~/profmedia/files/rapporten/2023/report-machine-learning-trading-algorithms.pdf> accessed 17 July 2024.

106 Federico Consulich and others, 'AI e Abusi di Mercato: Le Leggi della Robotica Si Applicano alle Operazioni Finanziarie?' (May 2023) Quaderni Giuridici Consob n. 29 <https://www.consob.it/documents/11973/201676/qg29.pdf/768199a2-e17c-ca8e-00a5-186da9a19f79?t=1685344502568> accessed 17 July 2024.

107 Financial Markets Standards Board (FMSB), 'Behaviour-Pattern Conduct Analysis: Market Misconduct through the Ages' (May 2022) <https://fmsb.com/wp-content/uploads/2022/05/22974_BCA_Report_2022_Interactive.pdf> accessed 17 July 2024.

that emerge in this context. By addressing these pressing issues, the dissertation opens new avenues for further research and fosters a more informed and effective approach to the regulation and governance of AI in financial markets, in order to promote a sustainable and resilient financial ecosystem that upholds market integrity, fairness, investor protection, and financial stability in the era of AI.

1.5 Dissertation Structure

This dissertation comprises nine chapters, structured into two main parts. Part I, titled 'Machine Learning, Market Manipulation, and Collusion in Capital Markets', spans Chapters 2 to 4. Next, Part II, titled 'Challenges in AI Trading Governance and Market Manipulation Regulation: Exploring Pathways Ahead', encompasses Chapters 5 to 9. Following this introduction, the subsequent chapters are organised as follows.

Chapter 2 delves into the evolution of AI generations in financial trading, highlighting the ongoing progress in ML-based applications. These advancements have enabled the development of increasingly sophisticated AI trading systems. Remarkably, it is also possible to research artificial trading agents thanks to specific ML paradigms, such as DRL methods. Hence, this chapter explores the techno-methodical attributes of these ML approaches for financial trading, highlighting the key challenges researchers and practitioners generally face within the Computational Finance domain. It serves as a basis for our subsequent analysis of the potential of AI trading to threaten market integrity through market manipulation and algorithmic forms of collusion.

Chapter 3 focuses on the emerging risks of market manipulation due to AI trading powered by ML methods. By categorising market manipulation into four distinct levels of human involvement, we shed light on the novel risks introduced by AI trading systems. We also conduct a proof-of-concept examination to demonstrate how DRL-based artificial trading agents could autonomously engage in market manipulation.

Similarly, Chapter 4 is devoted to assessing the emerging risks of collusion between competing trading algorithms in capital markets. In doing so, it explores the concept of 'algorithmic interconnectedness' and its role as a facilitator in fostering collusive behaviour. In examining the phenomenon of 'tacit' collusion among trading algorithms, this chapter draws insights from economic theories of algorithmic collusion and applies them to the context of DRL methods. This allows us to consider, albeit primarily from a conceptual standpoint, the novel risks of collusive behaviour among competing AI trading algorithms.

Chapter 5 provides an overview of the EU legal and regulatory framework governing algorithmic trading and relevant anti-manipulation laws. We also discuss the limitations of these pieces of legislation to address the new risks associated with AI trading. Importantly, Chapters 2 to 4 establish the normative framework for subsequent chapters in analysing the emerging deficiencies of current legal and derived regulatory regimes.

Chapter 6 examines legal issues of liability for AI-enabled market misconduct and harm, emphasising its significance in assessing the efficacy of the EU enforcement regime. Through a Law and Economics approach, we analyse the limitations of current anti-manipulation laws and enforcement mechanisms. Based on the limitations found, we propose policy recommendations to enhance the effectiveness of the EU enforcement regime of market conduct rules.

Moving to supervisory frameworks, Chapter 7 evaluates the EU's approach to market conduct supervision in the context of AI trading. This chapter discusses the growing challenges competent authorities face in ensuring effective surveillance of trading activities in integrated yet fragmented EU capital markets. Furthermore, we explore, in the context of supervisory technology, how the adoption of ML methods and tools can empower financial supervisors to detect sophisticated forms of market manipulation.

Chapter 8 addresses residual as well as more general issues concerning the governance and regulation of AI in capital markets trading. We review prominent legal theories as well as emerging regulatory approaches worldwide. Drawing inspiration from the EU AI Act, we propose a risk-based regulatory framework for AI trading applications, going beyond the currently predominant approach of technology neutrality, and examine its merits in ensuring effective and future-proof AI governance in finance.

Eventually, Chapter 9 concludes by summarising the main findings, outlining the research impact, and acknowledging the research limitations of this dissertation. This concluding chapter also sets the stage for future research in the rapidly evolving scientific field of AI governance and regulation in capital markets trading and finance more generally.

PART I

MACHINE LEARNING, MARKET MANIPULATION, AND COLLUSION IN CAPITAL MARKETS

2. AI Adoption in Financial Trading: Techno-Methodical Specificities and Associated Risks to Capital Markets

In this chapter, we delve into the world of automated trading and its profound impact on global finance. The analysis centres around the use of AI methods and techniques in algorithmic trading, exploring their implications for market efficiency, market integrity, and financial stability. As we venture further into the subject, it will become evident that ongoing progress in the research and practice of AI—particularly its subfield of ML—has been fundamentally revolutionising the financial trading industry.

Our examination begins with a brief conceptualisation of how AI adoption and its ramifications within the domain of algorithmic trading have contributed to the growing complexity of the capital markets system (Chapter 2.1). Subsequently, we more specifically delve into the evolution of different AI generations, starting from early deterministic approaches and moving to more recent ML-based applications (Chapter 2.2). Next, our focus shifts to ML, which underlies the most advanced AI applications for financial trading currently being researched and increasingly employed by market participants. A comprehensive understanding of the technical aspects of the various ML paradigms is a prerequisite for our subsequent analysis (Chapter 2.3). Building upon this foundation, we then introduce the latest generation of AI trading techniques, which this dissertation refers to as 'Deep Computational Finance'[108]—an emerging ML

[108] For the purpose of this dissertation, the term 'Deep Computational Finance' refers to the most recent applications in Computational Finance research and practice that, among innovative ML methods, leverage the use of DL. Computational Finance is a multidisciplinary field that encompasses the development, implementation, and application of mathematical and computational techniques to solve problems of a financial nature. It relies on the formulation and use of mathematical models and software programs to analyse and interpret financial data, enabling informed decision-making in the complex realm of finance. Cornelis A Los, *Computational Finance: A Scientific Perspective* (World Scientific 2001) 11-12. Computational Finance combines principles from Computer Science, Statistics, Information Systems, Financial Economics, and Mathematical Finance. *See* Argimiro Arratia, *Computational Finance: An Introduction Course with R* (Atlantis Press 2014) v. The field leverages advanced technological applications and methods, such as data mining, genetic algorithms, neural

paradigm based on DL as well as other innovative methods.[109] As will be argued, these innovative approaches facilitate the exploration of (autonomous) algorithmic trading agents by practitioners in the field (Chapter 2.4). Alongside the undeniable achievements of these technological advances and their promise for the industry, we also examine the uncertainties and risks they entail, including the often-discussed black box issue as well as other concerns associated with the use of ML methods (Chapter 2.5). Lastly, this chapter culminates in a concise summary of the key findings and concluding remarks, providing a cohesive overview of our exploration of AI in the context of financial trading (Chapter 2.6).

2.1 AI-Introduced Complexity in Global Capital Markets

When examining global capital markets through the lens of Complexity Theory[110], we can observe an evolutionary trendline towards greater system complexity[111].[112] Over

networks, ML, and Monte Carlo simulation, to address various challenges in finance, including risk management, asset allocation, trading strategies, forecasting, and option pricing. *See* Yaser S Abu-Mostafa and others, *Computational Finance* (The MIT Press 1999) 1-3.

[109] *See* Chapter 2.4.

[110] Complexity Theory is a multidisciplinary framework that seek to understand the behaviour and dynamics of complex systems. It is based on the concept that many natural and social phenomena are characterised by complex interactions and non-linear relationship, giving rise to emergent properties, unpredictable outcomes, and system instability. For a concise introduction to Complexity Theory, see Ilaria Capelli, 'The Complexity Theory and Financial Systems Regulation' in Sergio Abeverio and others (eds), *Complexity and Emergence: Lake Como School of Advanced Studies, Italy, July 22-27, 2018* (Springer Cham 2022) 50-52 <https://doi.org/10.1007/978-3-030-95703-2_2> accessed 17 July 2024.

[111] In physics, a 'complex system' is composed by a number of sub-units or parts that interact with each other through competitive, nonlinear collaboration leading to emergent, self-organised system behaviour, which in turn affects the behaviour of the individual parts. Jarosław Kwapień and Stanisław Drożdż, 'Physical Approach to Complex Systems' (2012) 515 Physics Reports 115, 117-118 <https://doi.org/10.1016/j.physrep.2012.01.007> accessed 17 July 2024.

[112] When applied to understanding market systems such as capital markets, Complexity Theory offers insights into the dynamics of the complex network of actors and their interactions. However, studying the behaviour of market participants requires considering not only the physical aspects of the system, but also the psychological dimension, which plays a significant role in decision-making processes within markets. The physical and psychological components are closely interconnected, shaping the overall behaviour of market participants and influencing the functioning of the market system. W Brian Arthur, 'Complexity in Economic and Financial Markets: Behind the Physical Institutions and Technologies of the Marketplace Lie the Belief and Expectations of Real Human Beings' (1995) 1(1) Complexity 20 <https://doi.org/10.1002/cplx.6130010106> accessed 17 July 2024. Applying

time, the complexity of capital markets as a system has expanded along different but interconnected dimensions.[113] Although complexity in finance is often discussed in terms of the sophistication of financial modelling techniques and the proliferation of newly engineered financial instruments,[114] it also encompasses the fast-changing and adaptive nature of the socio-technical system of capital markets. In this context, complexity pertains to the functioning and behaviour of markets, fuelled by all sorts of economic interrelationships among the various members of the heterogeneous category of market actors. These interactions are characterised by a highly dynamic and evolving nature, partially influenced by technological innovations.[115] In particular, technology has a key role in in defining the spatial and temporal dimensions and boundaries in which interactions between different actors take place in capital markets.[116]

Viewed from this perspective, it becomes apparent that technological innovation significantly contributes to increasing the overall complexity of the global financial system.[117] However, this complexity poses a challenge for financial regulation,

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Complexity Theory to observe and understand the global capital markets system, its operation and evolutionary dynamics, as well as the resulting implication for financial regulation is by no means a new idea. *See, e.g.*, Cheng-Yun Tsang, 'Rethinking Modern Financial Ecology and Its Regulatory Implications' (2017) 32(3) Banking & Finance Law Review 461 <https://www.proquest.com/scholarly-journals/rethinking-modern-financial-ecology-regulatory/docview/1935234592/se-2> accessed 17 July 2024.

113 *E.g.*, Matteo Marsili and Kartik Anand, 'Financial Complexity and Systemic Stability in Trading Markets' in Arthur M Berd (ed), *Lessons from the Financial Crisis: Insights from the Defining Economic Event of Our Lifetime* (Risk Books 2010) 455-461.

114 *See* Steven L Schwarcz, 'Regulating Complexity in Financial Markets' (2009) 87(2) Washington University Law Review 211, 216-230 <https://openscholarship.wustl.edu/law_lawreview/vol87/iss2/1> accessed 17 July 2024.

115 *See, e.g.*, Marsili and Anand (n 113) 455; Tsang (n 112), 470-473.

116 *See, e.g.*, Caitlin Zaloom, 'Time, Space, and Technology in Financial Networks' in Manuel Castells (ed), *The Network Society: A Cross-Cultural Perspective* (Edward Elgar Publishing 2004) 198-210.

117 *See, e.g.*, Kirilenko and Lo (n 49); Neil Johnson and others, 'Abrupt Rise of New Machine Ecology beyond Human Response Time' (2013) 3 Scientific Reports, Article 2627 <https://nature.com/articles/srep02627?proof=t2019-5-29> accessed 17 July 2024.

prompting the need to develop strategies to master it effectively. As detailed further, the rise of algorithmic trading and the subsequent innovation in this area spurred by AI is a glaring example of how technology increases complexity within financial markets.

A. The advent of algorithmic trading

The advent of electronic communication networks and computer systems has radically transformed the organisation and functioning of capital markets. This process of electronification has also fundamentally altered financial trading practices.[118] A striking example of this profound transformation is the shift from the old-fashioned open outcry system to electronic trading models.[119] Where traditionally financial transactions were negotiated and executed face-to-face by human professionals, contemporary financial trading is virtually driven in its entirety by automated trading through to the use of algorithmic systems.[120]

Innovation in trading technology has significantly reshaped market structures, expanding—if not multiplying—trading opportunities available to market participants. Technology has broken down geographical boundaries and enabled continuous

[118] *See, e.g.*, Franklin Allen, James McAndrews, and Philip Strahan, 'E-Finance: An Introduction' (2002) 22 Journal of Financial Services Research 5 <https://doi.org/10.1023/A:1016007126394> accessed 17 July 2024.

[119] *Instinet*, which went into operation in 1969, is widely considered as the world's inaugural electronic trading system. Subsequently, in 1971, the *NASDAQ* stock market emerged as the first electronic trading market allowing over-the-counter (OTC) trading of 2500 securities. *See* Peter Gomber and others, 'Competition Between Equity Markets: A Review of the Consolidation versus Fragmentation Debate' (2017) 31(3) Journal of Economic Surveys 792, 812 <https://doi.org/10.1111/joes.12176> accessed 17 July 2024.

[120] For a comparison between traditional open-outcry markets and electronic trading markets in terms of market liquidity and efficiency, see Marcel N Massimb and Bruce D Phelps, 'Electronic Trading, Market Structure and Liquidity' (1994) 50(1) Financial Analyst Journal 39 <https://doi.org/10.2469/faj.v50.n1.39> accessed 17 July 2024; *see also* Hans R Stoll, 'Electronic Trading in Stock Markets' (2006) 20(1) Journal of Economic Perspectives 153 <https://pubs.aeaweb.org/doi/pdfplus/10.1257/089533006776526067> accessed 17 July 2024.

interactions, resulting in increased trading volumes.[121] Many consider that these developments have had a positive impacts on market quality, bringing various benefits to the overall economy, such as increased liquidity and reduced transaction costs.[122] The manifestation of these benefits perhaps explains why the rise of algorithmic trading has been supported by specific regulations aimed at promoting competition among market participants at different levels and the development of more efficient markets.[123]

At the same time, there is also who believe that algorithmic trading—particularly HFT—has compromised market quality, favouring those participants who can exploit the advantages offered by the technology often at the expense of others.[124] The ultra-fast and interconnected nature of contemporary capital markets is often considered one of the main causes of increased risks to financial stability and market integrity.[125] However, in most advanced jurisdictions, *ad hoc* regulations have also being implemented in order to mitigate some of these risks, with a view at countering the adverse effects of flawed or malicious design, development, and use of algorithmic trading systems and strategies.[126]

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[121] *E.g.*, Helen Allen, John Hawkins, and Sestuya Sato, 'Electronic Trading and Its Implication for Financial Systems' in Morten Balling, Frank Lierman, and Andy Mullineux (eds), *Technology and Finance: Challenges for Financial Markets, Business Strategies and Policy Makers* (Routledge 2002) 219-224.

[122] *E.g.*, Terrence Hendershott, 'Electronic Trading in Financial Markets' (2003) 5(4) IT Professional Magazine 10 <https://doi.org/10.1109/MITP.2003.1216227> accessed 17 July 2024.

[123] For a research study on the role of financial regulation to foster innovation while safeguarding competition and other public goals, see Wolf-Georg Ringe and Christopher Ruof, 'Regulating Fintech in the EU: The Case for a Guided Sandbox' (2020) 11 European Journal of Risk Regulation 604 <https://doi.org/10.1017/err.2020.8> accessed 17 July 2024.

[124] *See, e.g.*, footnotes n. 52 and 66.

[125] *See, e.g.*, Victor Galaz and Jon Pierre, 'Superconnected, Complex and Ultrafast: Governance of Hyperfunctionality in Financial Markets' (2017) 3(2) Complexity, Governance & Network 12 <https://core.ac.uk/download/pdf/228973508.pdf> accessed 17 July 2024.

[126] One of the most active scholars in this area is certainly Professor Yesha Yadav, though she mainly focuses on the US legal regime. *See generally* Yesha Yadav, 'Algorithmic Trading and Market Regulation' in Walter Mattli (ed), *Global Algorithmic Capital Markets: High Frequency Trading,*

Given the institutional and organisational path dependencies associated with the transformation of capital markets due to the rise of algorithmic trading, it safe to believe that algorithms will play an increasingly pervasive role.[127] Moreover, thanks to continuous advances in AI—particularly ML—along with the increasingly widespread adoption of related trading techniques and tools, a further wave of radical transformation is currently ongoing, accounting for one of the most interesting developments in FinTech in the recent years.[128]

B. AI and algorithmic trading

The continuous progress in AI research and practice has strongly influenced the use of technology within the domain of algorithmic trading. Various organisations—such as asset management companies, credit institutions, investment firms, and other financial institutions—have embraced the adoption of AI solutions across a wide range of business functions. This growing trend is evident from regulatory reports, which highlight a notable increase in the use of ML methods by industry participants, demonstrating the growing significance of AI in the financial sector. [129] Industry reports

Dark Pools, and Regulatory Challenges (Oxford University Press 2018) 232-259 <https://doi.org/10.1093/oso/9780198829461.001.0001> accessed 17 July 2024. The topic has also attracted the attention of European scholars. *See, e.g.*, Busch (n 85); Čuk and Van Waeyenberge (n 70); Sadaf and others (n 98).

[127] *See* footnote n. 60.

[128] For a historical account of different FinTech waves in the history of global finance, see Arner, Barberis, and Buckley (n 45).

[129] *See, e.g.*, Bank of England (BoE) and UK Financial Conduct Authority (FCA), 'Machine Learning in UK Financial Services' (October 2019) 3, 8-9 <https://www.bankofengland.co.uk/-/media/boe/files/report/2019/machine-learning-in-uk-financial-services.pdf> accessed 17 July 2024 [hereinafter BoE and FCA I], reporting that among the 106 UK financial institutions surveyed, two-thirds have already made some use of ML in their business operations in 2019; Cambridge Centre for Alternative Finance and World Economic Forum (WEF), 'Transforming Paradigms: A Global AI in Financial Services Survey' (2020) <http://www3.weforum.org/docs/WEF_AI_in_Financial_Services_Survey.pdf> accessed 17 July 2024, surveying approximately 150 financial firms across thirty-three different countries, revealing that 77 percent of all respondents believe that AI will be critical to their business models by 2023; IOSCO, 'The Use of Artificial Intelligence and Machine Learning by Market Intermediaries and Asset Managers' (September 2021) Final Report, FR06/2021, 6-8 <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD684.pdf> accessed 17 July 2024, reporting a rising trend in the use of AI and ML by market intermediaries and asset managers; BoE and FCA,

further reveal that the majority of traders at investment firms believe that AI/ML technologies will play a key role in shaping the future of financial trading.[130] This belief is reflected in the substantial investments made in AI solutions, with a year-over-year positive increase of 208 percent recorded between 2021 and 2021.[131]

The advantages offered by AI applications powered by ML are mainly twofold. On one hand, these tools enable companies to allocate economic resources and make financial decisions more operationally efficient under conditions of uncertainty. Thus, a masterful use of AI and related technologies can ensure a competitive edge over rival firms.[132] On the other, the widespread adoption of AI solutions within the industry can also translate into more favourable market conditions and improved allocative efficiency, which in turn can benefit both consumers, investors, and society at large.[133] At the same time, however, AI also poses a number of challenges to ensure trustworthy application. In particular, if adequate governance and regulatory frameworks are not

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'Machine Learning in UK Financial Services' (October 2022) <https://www.bankofengland.co.uk/report/2022/machine-learning-in-uk-financial-services> accessed 17 July 2024 [hereinafter BoE and FCA II], reporting that 72 percent of surveyed firms declared either using or developing ML applications, also suggesting that an upward trend is expected as firms anticipate a substantial increase in ML adoption by 2025; AFM (n 105) 12, reporting that 80-100 percent of trading firms under AFM supervision employ ML methods; Giulio Bagattini and Claudia Guagliano, 'Artificial Intelligence in EU Securities Markets' (1 February 2023) ESMA TRV Risk Analysis, ESMA50-164-6247, 4-8 <https://www.esma.europa.eu/sites/default/files/library/ESMA50-164-6247-AI_in_securities_markets.pdf> accessed 17 July 2024, however noting that "*detailed evidence on recent developments as regards the use of AI in European financial markets is scarce*".

130 JP Morgan, 'The e-Trading Edit: Insight from the inside' (23 January 2023) <https://www.jpmorgan.com/markets/etrading-trends> accessed 17 July 2024, surveying a total of 835 institutional traders.

131 *See* NVIDIA, 'State of AI in Financial Services: 2022 Trends' (2022) Survey Report, 4 <https://www.nvidia.com/content/dam/en-zz/Solutions/industries/finance/ai-financial-services-report-2022/fsi-survey-report-2022-web-1.pdf> accessed 17 July 2024.

132 *See, e.g.*, Financial Stability Board (FSB), 'Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications' (1 November 2017) 24-25 <www.fsb.org/wp-content/uploads/P011117.pdf> accessed 17 July 2024.

133 *E.g.*, ibid 25-27.

in place to support safe and responsible AI adoption, the overall quality and stability of the financial system could be at risk.[134]

Undoubtedly, the use of ML by financial institutions to automate trading and investment activities exemplifies how the field of AI is fuelling a growing trend towards greater complexity in capital markets.[135] With AI trading transforming the business operations and market interactions of market participants due to ML, it fundamentally impacts their collective behaviour, thereby reshaping the very functioning of capital markets. Hence, the growing sophistication of algorithmic trading practices, along with the businesses and industries surrounding them, has introduced an additional layer of complexity on top of a dynamic system—i.e. global capital markets—that naturally tends to be quite complex anyway.[136]

Within this trend towards increased system complexity, however, there are also some negative aspects that need to be considered. On one hand, mastering complexity is of great importance for market players such as financial institutions, which are called to make informed business decisions in the face of uncertainty while adhering to capital markets regulation. On the other hand, financial regulators and supervisors must take utmost account of the complexity stemming from AI trading-dominated capital markets. Particularly, they need to navigate the technical and related regulatory aspects of this additional source of system complexity to fulfil their institutional mandates effectively, which include promoting market efficiency, safeguarding financial stability, and protecting investors and market integrity.

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134 Several regulatory reports highlight risks to financial stability as one of the main threats of AI. *See* footnotes n. 129 and 132.

135 *Cf*. IOSCO (n 129) 1-3; OECD, 'Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges, and Implications for Policy Makers' (2021) 21-29 <https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf> accessed 17 July 2024.

136 *Cf*. Hilbert Martin and David Darmon, 'How Complexity and Uncertainty Grew with Algorithmic Trading' (2020) 22(5) Entropy 499 <https://doi.org/10.3390/e22050499> accessed 17 July 2024.

Hence, to better navigate the increased complexity resulting from ongoing progress in AI trading technology, as well as the resulting implications for the governance and regulation of algorithmic trading, the following provides an overview of various AI generations and their impact on financial trading practices.

2.2 The Different AI Generations in Algorithmic Trading

From a historical perspective, algorithmic trading can be viewed as one of the pioneering applications where AI techniques were implemented.[137] Over the years, a wide range of AI methods and techniques have been researched and applied to financial trading.[138] In an algorithmic trading system, AI tools can be employed to optimise different aspects of the trading cycle. These include pre-trade analysis, trading strategy selection, order routing and execution management, as well as post-trade analysis.[139] By leveraging AI, human traders can enhance their decision-making processes, improve efficiency, and potentially achieve better trading outcomes.[140]

Following the categorisation provided in *Table 1* below, in the subsequent sub-sections we examine the different generations of AI approaches in financial trading. We will begin by exploring early AI applications, such as 'expert systems', which laid the groundwork for subsequent advancements. Subsequently, we will delve into the realm of those AI applications characterising the 'first ML era' in financial trading.

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137 *Cf.* Dave Cliff, Dan Brown and Philip Treleaven, 'Technology Trends in the Financial Markets: A 2020 Vision' (UK Government Office for Science, 2011) <https://webarchive.nationalarchives.gov.uk/ukgwa/20121212135622/http://www.bis.gov.uk/assets/bispartners/foresight/docs/computer-trading/11-1222-dr3-technology-trends-in-financial-markets.pdf> accessed 17 July 2024.

138 *See* footnote n. 152.

139 For a comprehensive overview on algorithmic trading systems, their different components and operational functioning, *see generally* Treleaven, Galas, and Lalchand (n 49) 78-84; *see also* Fethi A Rahbi, Nikolay Mehandjiev, and Ali Baghdadi, 'State-of-the-Art in Applying Machine Learning to Electronic Trading' in Benjamin Clapman and Jascha-Alexander Koch (eds), *Enterprise Applications, Markets and Services in the Financial Industry: 10th International Workshop, FinanceCom 2020, Helsinki, Finland, August 18, 2020, Revised Selected Papers* (Springer Cham 2020) 3-20.

140 Ibid.

Finally, we will explore the so-called 'Deep Computational Finance'—encompassing most recent ML approaches based on DL and other innovative methods—, which has further expanded the frontiers of AI trading. By delving into these three different AI generations, we seek to illuminate the evolution and impact of AI applications in the domain of financial trading.

Table 1: A categorisation of AI generations in financial trading

AI Generation	Time Period	AI Methods
Early generation (i.e. GOFAI)	1980 – 2000 ca.	Deterministic AI systems (i.e. 'rule-based' or 'expert systems')
Intermediate generation (i.e. the 'First ML era')	2000 – 2010 ca.	AI systems based on ML methods (i.e. 'supervised learning', 'unsupervised learning', and 'reinforcement learning')
Latest generation (i.e. 'Deep Computational Finance')	From 2010 ca.	AI systems based on DL and other innovative methods

A. 'Good-old-fashioned AI'

Since the inception of algorithmic trading, industry players have been increasingly embraced the application of AI tools to improve their business operations, seeking to capitalise on various efficiency gains in terms of performance, risk management, cost reduction, and more.[141] Originally, algorithmic trading systems featured basic AI

[141] *See generally* Giacomo Calzolari, 'Artificial Intelligence Market and Capital Flow – AI and the Financial Sector at Crossroads' (May 2021) Study Requested by the AIDA committee, European Parliament, PE 662.912, 21 <https://www.europarl.europa.eu/RegData/etudes/STUD/2021/662912/IPOL_STU(2021)662912_EN.pdf> accessed 17 July 2024.

techniques, known as ‘rule-based’ or ‘expert-systems’. These early AI approaches, often referred to as ‘good-old-fashioned-AI’[142] (GOFAI), were relatively rudimentary in their algorithmic inner workings, as they relied on human experts’ specific domain knowledge and assumptions, tacit and explicit, encoded in computer programmes.[143]

One of the main limitations of GOFAI trading applications is their deterministic approach in assisting human experts in making financial decisions. These ‘rule-based’ or ‘expert systems’ typically operate on the basis of ‘if/then’ rules, where algorithms follow strictly defined commands and pre-defined strategies.[144] However, rule-based algorithmic trading has its drawbacks. The trading strategies are built on the specific domain knowledge of human experts applied to historical data and patterns. This approach may not always be effective in anticipating future market conditions, thus, may not perform well when confronted with the dynamic and unpredictable nature of market prices.[145]

Although this first generation of AI methods applied to financial trading may seem elementary, ensuring their proper functioning can pose considerable challenges for users.[146] Due to their system complexity and level of interconnectedness within highly fast and dynamic market environments, algorithmic trading systems generally

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[142] The term seems to have been first used in the context of AI-related philosophical studies. *See* John Haugeland, *Artificial Intelligence: The Very Idea* (MIT Press 1985) 112. For an introduction to GOFAI, see Margaret A Boden, ‘GOFAI’ in Keith Frankish, Milton Keynes, and William M Ramsey (eds), *The Cambridge Handbook of Artificial Intelligence* (Cambridge University Press 2014) 89-107 <https://doi.org/10.1017/CBO9781139046855.007> accessed 17 July 2024.

[143] *See* Roy S Freedman, ‘AI on Wall Street’ (1991) 6(2) IEEE Intelligent Systems 3 <https://doi.ieeecomputersociety.org/10.1109/64.79702> accessed 17 July 2024.

[144] *See* Crina Grosan and Ajith Abraham, *Intelligent Systems: A Modern Approach* (Springer Cham 2011) 149; *see also* Treleaven, Galas, and Lalchand (n 49) 80-81.

[145] *See, e.g.*, Narayana Darapeni and others, ‘Automated Portfolio Rebalancing using Q-Learning’ in *2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, NY, USA, 28-31 October 2020* (IEEE 2020) 0596 <https://doi.org/10.1109/UEMCON51285.2020.9298035> accessed 17 July 2024.

[146] *See, e.g.*, Treleaven, Galas, and Lalchand (n 49) 77-78 and 85; Yadav (n 65) 1069-1070; Yadav (n 126) 237-240.

make it difficult to fully understand the motives behind their operations or to derive insights from their inner workings, even allowing for the inspection of their code.[147] Consequently, also the oversight of their trading conduct and the enforcement of market conduct rules by public authorities become more complicated.[148] In the latter regard, algorithmic trading often renders established liability rules—which are based on traditional legal concepts such as 'causation', 'foreseeability', 'negligence', and 'intent'—not entirely applicable.[149] As will be argued in more detail in Chapter 6 and Chapter 7, respectively, more advanced AI approaches, based on ML, further complicates issues related to the enforcement and supervision of market conduct rules.

B. The advent of the first ML era

In more recent years, thanks to ML, a new generation of AI trading applications has emerged. This development can be attributed to two primary factors, which are concatenated and path-dependent. First, use of ML in financial trading is driven by the specific business needs of market participants, partly aimed at better serving their clients.[150] Investment firms, in particular, have embraced ML for various innovative tasks, including the development of cutting-edge algorithmic trading systems and strategies.[151] Examples abound, such as ML applications for automating sentiment analysis from social media content, examining financial reports and other documents,

[147] *See, e.g.*, Yadav (n 126) 240-241.

[148] *See, e.g.*, ibid 251-252.

[149] *See, e.g.*, footnotes n. 76 and 77.

[150] *See, e.g.*, FSB (n 132) 7-10; IOSCO (n 129) 6-8; and OECD (n 135) 19-20.

[151] These include strategies such as: (i) signal processing, the art of filtering meaningful information from noisy data to discern trading patterns; (ii) market sentiment analysis, a strategy that extrapolates markets appetite for trading by learning from market activity; (iii) news reader, which leverages on the role of news from different media to look for investment opportunities; and (iv) pattern recognition, or the computational ability to learn from changing price patterns on markets how to classify different market prices dynamics in order to anticipate price movements to gain a profit. Bonnie G Buchanan, 'Artificial Intelligence in Finance' (The Alan Turing Institute 2019) 16 <https://www.turing.ac.uk/sites/default/files/2019-04/artificial_intelligence_in_finance_-_turing_report_0.pdf> accessed 17 July 2024.

and visual chart analysis. Additionally, ML methods facilitate the optimisation of multiple tasks within the trading cycle (e.g., pre-trade analysis, trading signal generation, trade execution, etc.). The most sophisticated applications even involve the research of artificial trading agents.[152]

Second, the progress in ML applications has been facilitated by parallel advancements in information and communication technology (ICT) products, services, and solutions related to AI.[153] Specifically, the computational power and data storage capabilities have become more affordable and accessible, with technology providers offering outsourcing services, such as cloud computing[154] and Software-as-a-Service (SaaS)[155], including AI-as-a-Service[156] (AIaaS).[157] Additionally, the availability of data that algorithms can process to inform trading and investment decisions has exploded due to both market and regulatory developments.[158] In fact, the proliferation of markets

152 *See, e.g.*, Longbing Cao, 'AI in Finance: Challenges, Techniques, and Opportunities' (2022) 55(3) ACM Computing Surveys, Article 64 <https://doi.org/10.1145/3502289> accessed 17 July 2024.

153 *E.g.*, FSB (n 132) 7-8.

154 Cloud computing refers to the provision of on-demand computing services, including storage, processing power and other software applications via the Internet. Unlike reliance on local servers or personal devices, cloud computing allows users to access and use resources remotely through a network of servers hosted in data centres by private companies. For a discussion on the role of cloud computing in financial services and the possible effects on this sector, see Richard Harmon and Andrew Psaltis, 'The Future of Cloud Computing in Financial Services: A Machine Learning and Artificial Intelligence Perspective' in Mohammad Zoynul Abedin and others (eds), *The Essentials of Machine Learning in Finance and Accounting* (Routledge 2021) 123-138.

155 SaaS is a cloud computing model where software applications are provided as a service over the Internet. Users can therefore access and use software applications without the need to install and maintain these on their local devices. As a cloud computing service, SaaS software is centrally hosted and managed by a service provider, who is responsible for the infrastructure, security, updates, and assistance.

156 AIaaS is also based on a cloud computing model offering AI resources as a service. Users of AIaaS can leverage ore-built AI algorithms, model, and tools provided by the service provider without the need for direct investment in infrastructure or expertise.

157 *See generally* Cliff, Brown, and Treleaven (n 137); IOSCO, 'IOSCO Research Report on Financial Technologies (Fintech)' (February 2017) 6-7 <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD554.pdf> accessed 17 July 2024.

158 *E.g.*, FSB (n 132) 9.

and financial assets negotiated therein, coupled with the overall acceleration of financial trading, has resulted in a massive volume of granular and high-frequency data generated every day. Automated trading technology can leverage this vast amount of data, which may no longer be intelligible to the human mind, to identify profitable investment opportunities.[159] Beyond traditional financial data, 'alternative data'[160] (or AltData) has gained increasing importance in this context.[161] Moreover, the accessibility to ML methods, libraries, and toolkit has also improved—in part thanks to the availability of open access platforms like GitHub[162] and the emergence of SaaS solutions—, thus facilitating the widespread adoption of innovative ML applications, as opposed to more traditional GOFAI approaches, to perform complex financial problem-solving and task execution.

Sophisticated global market players, who notoriously require timely information and advanced analytical power to navigate the uncertainty of financial markets and identify profitable opportunities, are already extensively employing ML in their trading activities.[163] Looking to the future, the adoption of AI/ML in financial

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[159] *E.g.*, ibid 18, reporting on the use of AI and ML by financial institutions to devise trading and portfolio management strategies.

[160] For a reference material on 'alternative data', see Denev Alexander and Saeed Amen, *The Book of Alternative Data: A Guide for Investors, Traders, and Risk Managers* (John Wiley & Sons 2020); *see also* Marko Kolanovic and Rajesh T Krishnamachari, *Big Data and AI Strategies: Machine Learning and Alternative Data Approach to Investing* (JP Morgan May 2017) 28-50 <https://cpb-us-e2.wpmucdn.com/faculty.sites.uci.edu/dist/2/51/files/2018/05/JPM-2017-MachineLearningInvestments.pdf> accessed 17 July 2024, providing a comprehensive overview of different kinds of alternative data, their taxonomy, and possible use for specific trading strategies.

[161] *See* Marcos López de Prado, *Advances in Financial Machine Learning* (Wiley, 2018) 23-25.

[162] The 'GitHub' community allow users to discuss, interact with and collaborate on software projects. More information is available at: <https://github.com/community> accessed 17 July 2024.

[163] In addition to benefiting market participants who can make profitable use of innovative technologies, FinTech, including innovative business models based on AI, could lead to a democratisation of financial services to the benefit of retail investors and consumers in general. *See, e.g.*, Christoph F Breidbach, 'Fintech: Research Directions to Explore the Digital Transformation of Financial Service Systems' (2019) 30(1) Journal of Service Theory and Practice 79, 92 <https://ssrn.com/abstract=3649758> accessed 17 July 2024; Joe McKendrick, 'The Coming Democratization of Financial Services, Thanks to Artificial Intelligence' (*Forbes*, 14 January 2023) <https://www.forbes.com/sites/joemckendrick/2023/01/14/the-coming-democratization-of-financial-services-thanks-to-ai> accessed 17 July 2024; Edouard A Ribes, 'Transforming Personal

trading is expected to continue to be widespread and even increase. Unlike previous generations, ML allows for the development of trading algorithms and strategies that are more adaptable to changing market conditions, operating at varying levels of autonomy.[164] In the following section, we provide a high-level overview of the main ML paradigms currently employed by the most technologically sophisticated market players.

2.3 ML and Algorithmic Trading

ML, as a subfield of AI, encompasses a diverse range of learning paradigms through software algorithms.[165] ML algorithms possess the remarkable ability to autonomously acquire knowledge from input data, thereby limiting the need for constant human control and oversight. This self-learning capability can be realised through several possible approaches: (i) human experts-assisted training, (iii) independent interaction of the algorithm within a domain-specific environment, or (iii) hybrid methods.[166]

Within the realm of finance, ML offers exciting opportunities for investment firms to optimise operational tasks and streamline processes throughout the trading cycle. ML-based systems hold the potential to augment or even replace the traditional roles performed by human agents in both cognitive tasks, such as pattern recognition,

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Finance Thanks to Artificial Intelligence: Myth or Reality?' (2023) 2(1) Financial Economics Letters 11 <https://doi.org/10.58567/fel02010002> accessed 17 July 2024.

[164] *See, e.g.*, BoE and FCA I (n 129) 2; Kolanovic and Krishnamachari (n 160) 9-11.

[165] For an introductory exploration of various machine learning models and their applications in algorithmic trading, see Adriano Koshiyama, Nick Firoozye, and Philip Treleaven, 'Algorithms in Future Capital Markets' in *ICAIF '20: Proceedings of the First ACM International Conference on AI in Finance, October 2020* (ACM 2021) Article 14 <https://doi.org/10.1145/3383455.3422539> accessed 17 July 2024.

[166] *Cf.* Eduardo Mosqueira-Rey and others, 'Human-in-the-loop machine learning: a state of the art' (2023) 56 Artificial Intelligence 3005 <https://doi.org/10.1007/s10462-022-10246-w> accessed 17 July 2024. Through a comprehensive analysis, the authors shed light on the vast and growing landscape of learning approaches. Their rigorous examination not only clarifies the prevailing confusion within current scientific research but also presents a novel classification of existing techniques, based on the various forms of interaction that can occur between humans and ML systems.

and financial decision-making.[167] In this context, ML empowers human experts to research algorithmic trading systems and strategies capable of exploring and identifying, with increased autonomy, profitable investment and trading opportunities, thus surpassing the cognitive limitations of the human mind alone.[168]

The various paradigms of ML can be categorised based on the specific type of human experts' involvement across the various stages of the learning process, including data labelling, model selection, hyperparameter tuning, monitoring, and other related aspects.[169] In the following, we outline and elucidate the three basic ML paradigms and their application in the financial trading domain.

A. Supervised Learning

In 'Supervised Learning' (SL), computer algorithms undergo training using empirical data that has been pre-labelled by human experts. This means that during the training phase, the correct outputs for all training data are known in advance, as opposed to the subsequent stages of validation and testing. The goal is to enable the algorithm to learn a function that effectively maps from input to output.[170] However, it is crucial to subject the learned generalised rule to meticulous validation and testing procedures before applying it, for instance, to predictive trading tasks, ensuring its reliability and accuracy.[171]

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[167] *See, e.g.*, Yun-Cheng Tsai and others, 'Financial Vision-Based Reinforcement Learning Trading Strategy' (2022) 1 Analytics 35, 35-37 <https://doi.org/10.3390/analytics1010004> accessed 17 July 2024.

[168] *See, e.g.*, Ali Shavandi and Majik Khedmati, 'A Multi-Agent Deep Reinforcement Learning Framework for Algorithmic Trading in Financial Markets' (2022) 208 Expert Systems with Applications, Article 118124, 2 <https://doi.org/10.1016/j.eswa.2022.118124> accessed 17 July 2024.

[169] *Cf.* Russell and Norvig (n 14) 669-671; *see also* Mosqueira-Rey and others (n 166).

[170] *See* Russell and Norvig (n 14) 671; Kolanovic and Krishnamachari (n 160) 18.

[171] *See* Russell and Norvig (n 14) 671-674.

SL methods primarily serve as computational tools suitable for statistical regression and classification purposes.[172] For instance, a human trader can provide an SL algorithm with a rich dataset encompassing historical market data, such as assets prices, returns, and volatility, as well as technical market indicators or other relevant information. By training the algorithm on this data, the ultimate objective is to predict the future price movement of a given financial instrument.[173] This prediction can hence be used to inform subsequent investment or trading decision. Additionally, SL algorithms can be used to classify different assets based on specific distinguishing criteria, derived from past observations and empirical data, such as analysing their past performance or assessing their associated risks.[174]

B. Unsupervised Learning

In 'Unsupervised Learning' (UL), algorithms are employed to infer patterns and regularities from input data by identifying similar yet distinctive features, often with limited or no human feedback.[175] These methods prove particularly valuable for tasks such as cluster analysis and dimensionality reduction, especially when dealing with

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[172] *See, e.g.*, Kolanovic and Krishnamachari (n 160) 57 and 77, discussing, in technical detail, the functioning of supervised learning methods for regression and classification purposes; FSB (n 132) 5.

[173] For example, SL methods have been applied to forecast financial time-series of stock price. *See, e.g.*, Kyoung-Jae Kim, 'Financial Time Series Forecasting Using Support Vector Machines' (2003) 55(1-2) Neurocomputing 307 <https://doi.org/10.1016/S0925-2312(03)00372-2> accessed 17 July 2024.

[174] For example, SL methods can be applied to classify firms in financial distress based on pre-classified features using expert knowledge. *See* Fengyi Lin and others, 'Novel Feature Selection Methods to Financial Distress Prediction' (2014) 41(5) Expert Systems with Applications 2472 <https://doi.org/10.1016/j.eswa.2013.09.047> accessed 17 July 2024.

[175] *See* Russell and Norvig (n 14) 671.

high-dimensional data,[176] where pre-labelled information from human experts may be limited or non-existent.[177]

For instance, a human trader can leverage UL methods to conduct a pre-trade cluster analysis on a portfolio of financial instruments, grouping them based on their likelihood of generating positive daily returns in light of past observations. This analysis can then inform trading and investment decision-making processes.[178] It is important to note that SL and UL methods can be effectively integrated within the same algorithmic trading system to tackle different trading tasks. For instance, an UL algorithm can preliminarily perform a cluster analysis to extract meaningful features from the data, thereby identifying potential trading opportunities. The result obtained from the UL component can then be passed as input data to the SL component for further computational steps, such as stock price prediction.[179]

The integration of SL and UL methods allows an algorithmic trading system to generate trading signals and, based on this information, act on markets through a sequence of computational steps. Although both SL and UL methods contribute to automating tasks within the trading cycle, achieving full autonomy in algorithmic

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176 *See* Kolanovic and Krishnamachari (n 160) 93-95; Ira Assent, 'Clustering high dimensional data' (2012) 2(4) Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 340 <https://doi.org/10.1002/widm.1062> accessed 17 July 2024.

177 *See* Rodolfo C Cavalcante and others, 'Computational Intelligence and Financial Markets: A Survey and Future Directions' (2016) 55 Expert Systems with Applications 194, 201 and 207 <https://doi.org/10.1016/j.eswa.2016.02.006> accessed 17 July 2024; Kolanovic and Krishnamachari (n 160) 18.

178 *See, e.g.*, Mansoor Momeni, Maryam Mohseni, and Mansour Soofi, 'Clustering Stock Market Companies Via K-Means Algorithms' (2015) 4(5) Kuwait Chapter of Arabian Journal of Business and Management Review 1 <https://doi.org/10.12816/0018959> accessed 17 July 2024.

179 For an early research study that explores a hybrid strategy combining SL and UL, see Cheng-Lung Huang and Cheng-Yi Tsai, 'A Hybrid SOFM-SVR with a Filter-Based Feature Selection for Stock Market Forecasting' (2009) 36 Expert Systems with Applications 1529 (2009) <https://doi.org/10.1016/j.eswa.2007.11.062> accessed 17 July 2024. This research study incorporates an UL algorithmic component to perform filter-based feature selection, which helps identify important input attributes. Subsequently, a SL algorithm is employed to predict stock market prices based on the selected features.

trading systems remains a challenge. To be effective in real life applications, these methods still require some level of human assistance to adapt to changing market conditions, including scenarios involving tail risk and unforeseen market events.[180] Their main theoretical limitation stems from the empirical nature of the data they rely upon to develop domain-specific knowledge. In contrast, human traders, despite drawing insights from past experiences, also incorporate hard-to-explain intuitions and gut feeling when making decisions under conditions of uncertainty.[181] Although these human attributes do not necessarily guarantee trading success, they nevertheless offer a degree of flexibility in the face of adverse or unforeseen market events.

C. Reinforcement Learning

The third main ML paradigm, known as 'Reinforcement Learning' (RL), can offer solutions to address some of the limitations encountered by applications based on SL

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180 For an insightful perspective on the challenges of using supervised learning methods in trading and investment, see John Moody and others, 'Performance Functions and Reinforcement Learning for Trading Systems and Portfolios' (1998) 17 Journal of Forecasting 441, 442 <https://doi.org/10.1002/(SICI)1099-131X(1998090)17:5/6%3C441::AID-FOR707%3E3.0.CO;2-%23> accessed 17 July 2024. The authors highlight the fundamental misalignment between the optimisation goal of SL methods, which is limited to historical data observations, and the broader objectives of general investors who face dynamic constraints in evolving market conditions; *see also* Quang-Vinh Dang, 'Reinforcement Learning in Stock Trading' in Hoai An Le Thi and others (eds), *Advanced Computational Methods for Knowledge Engineering* (Springer Cham 2019) 311-312 <https://doi.org/10.1007/978-3-030-38364-0_28> accessed 17 July 2024. The chapter highlights the inadequacy of SL methods in handling time-delayed rewards, as they focus on achieving the best prediction at a specific point in time without considering delayed rewards or punishments. As such, SL methods applied to financial decision-making can only provide actionable recommendations rather than fully autonomous and effective automated trading systems.

181 For a behavioural economics research study exploring the influence of emotions on the decision-making and performance of professional traders, see Mark Fenton-O'Creevy and others, 'Thinking, Feeling and Deciding: The Influence on the Decision Making and Performance of Traders' (2011) 32 Journal of Organizational Behavior 1044 <https://doi.org/10.1002/job.720> accessed 17 July 2024. This research examines how emotions impact the decision-making processes of traders and their overall performance. It reveals that experienced traders possess a heightened meta-cognitive engagement with emotion regulation, enabling them to discern the relevance of emotions in relation to specific decisions and effectively manage them to enhance performance. *But see* Andrew W Lo, Dmitry V Repin, and Brett N Steenbarger, 'Fear and Greed in Financial Markets: A Clinical Study of Day-Traders' (2005) 95(2) American Economic Review 352 <https://doi.org/10.1257/000282805774670095> accessed 17 July 2024. The study suggests that emotions may have a negative impact on trading performance, and, conversely, successful trading may be attributed to a reduced level of emotional reactivity. This research offers insights into the potential pitfalls of emotional influences in trading decisions.

and UL algorithms.[182] RL serves as the foundational ML paradigm for developing autonomous software agents[183], whose knowledge and behaviour develop through self-learning from experience, guided by reinforcement signals in the forms of rewards and punishments.[184] RL-based agents strive to learn the best course of action, known as the 'policy action'[185], by optimising a pre-defined objective formulated as a cost or utility function. This optimisation process involves dealing with an uncertain and dynamic environment through a trial-and-error approach. In doing so, RL agents face a delicate and constant trade-off between 'exploration' and 'exploitation', in space and/or time of a particular domain, as they must *exploit* past actions for maximum rewards while also being able to *explore* new policies for improved decision-making in the future.[186]

The classification of various RL applications follows the specific optimisation methods employed in the self-learning process.[187] For all RL systems, however, human experts need to make critical *ex-ante* design choices to ensure trustworthy applications. These choices encompass defining the tasks assigned to RL agents, specifying the

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182 For a comprehensive introduction to the field of RL and its methods, see Richard S Sutton and Andrew G Barto, *Reinforcement Learning: An Introduction* (A Bradford Book 2018).

183 *See* footnote n. 17.

184 *See* Sutton and Barto (n 182) 1-5; *see also* Russell and Norvig (n 14) 840-842.

185 In the context of RL, a 'policy action' refers to the mapping of states of the world to the set of actions available to an RL agent. The purpose of this mapping is to maximise the agent's cumulative reward over the long term, which represents its overall strategy. RL agents aim to learn from past observations, including actions taken and rewards received, in order to approximate an optimal policy. *E.g.*, Arthur Charpentier, Romuald Élie, and Carl Remlinger, 'Reinforcement Learning in Economics and Finance' (2023) 62 Computational Economics 425, 427 <https://link.springer.com/article/10.1007/s10614-021-10119-4> accessed 17 July 2024.

186 *See* Sutton and Barto (n 182) 19-35.

187 The core idea behind different RL methods is to construct a mathematical model capable of planning future actions while considering the impact of those actions on the environment. However, a significant challenge in developing RL methods lies in obtaining meaningful data to formalise the mathematical problem. For a detailed discussion on the three main paradigms of RL (the 'critic', 'actor-only', and 'actor-critic' paradigms) and how they address the mathematical challenges of modelling components such as 'state', 'action', and 'space', see ibid 3-35.

available actions,[188] and formulating other technical aspects such as the 'reward function' and the 'value function', in mathematical terms.[189] The 'reward function' acts in the short term by providing immediate reward signals to RL agent following their individual actions. It is thus instrumental in guiding the learning process and determining the best policy actions.[190] However, since rewards alone do not suffice for achieving long-term goals, the 'value function' is employed to capture the long-term implications of agents' behaviour. It combines the immediate expected reward for a specific action with the cumulative long-term rewards based on the assumption of adhering to the best policy.[191] It is noteworthy that misspecification of these technical components, particularly the reward function, can lead to unintended consequences, rendering RL applications unreliable, unpredictable, and potentially hazardous within specific domains of application.[192]

Nevertheless, considering the dynamic, partially unknown, and unpredictable nature of the global financial system, RL has garnered significant scientific interest as a suitable approach for its application in this domain.[193] Given the challenges faced by humans in accurately predicting the behaviour of capital markets, researchers are experimenting with alternative methods to design intelligent machines capable of

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188 *See* Minseok Kong and Jungmin So, 'Empirical Analysis of Automated Stock Trading Using Deep Reinforcement Learning' (2023) 13(1) Applied Sciences, Article 633, 2 <https://www.mdpi.com/2076-3417/13/1/633> accessed 17 July 2024.

189 *E.g.*, Sutton and Barto (n 182) 7.

190 Ibid.

191 Ibid 8; Frensi Zejnullahu, Maurice Moser, and Joerg Osterrieder, 'Applications of Reinforcement Learning in Finance: Trading with a Double Deep Q-Network' (2022) arXiv preprint 1, 5 <https://arxiv.org/pdf/2206.14267.pdf> accessed 17 July 2024.

192 *See* OpenAI, 'Faulty Reward Functions in the Wild' (21 December 2016) <https://openai.com/research/faulty-reward-functions> accessed 17 July 2024; Thomas K Gilbert and others, 'Choices, Risks, and Reward Reports: Charting Public Policy for Reinforcement Learning Systems' (2022) Center for Long Term Cybersecurity White Paper Series, UC Berkley, February 2022 <https://cltc.berkeley.edu/wp-content/uploads/2022/02/Choices_Risks_Reward_Reports.pdf> accessed 17 July 2024.

193 *E.g.*, Charpentier, Élie, and Remlinger (n 185) 454.

acquiring knowledge about market trends and autonomously engaging in trading activities. The field of Computational Finance has witnessed an expanding body of literature that highlights the potential of RL methods in addressing various financial trading tasks.[194] These tasks encompass areas such as risk management, portfolio optimisation, option pricing, hedging, market making, smart order routing, trading execution, and robo-advising.[195] This growing body of research serves as evidence of the promising prospects for RL-based techniques to enhance decision-making and performance in investments and financial trading.

Unlike the ML methods discussed earlier, which focus primarily on generalisation, RL enables the creation of trading agents that actively explore their environment and learn optimal trading strategies.[196] These RL agents must consider real market constraints, such as liquidity, transaction costs, and market impact while aiming to maximise profit under some sort of risk control.[197] Specifically, the main goal of RL-based trading agents is to solve dynamic optimisation problems.[198] In the area of asset management, for instance, the use of RL allows to integrate forecasting and portfolio construction tasks within a unique system, thereby aligning the RL

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194 Ibid 454-456. For a comprehensive overview of RL methods applied to financial trading, see Thomas G Fischer, 'Reinforcement Learning in Financial Markets—A Survey' (2018) Friedrich-Alexander-Universität Erlangen-Nürnberg, Institute for Economics, Working Paper No. 12 <http://hdl.handle.net/10419/183139> accessed 17 July 2024. This review offers valuable insights into the application of RL algorithms and their potential for optimising trading strategies in the financial domain.

195 *See, e.g.*, Ben Hambly, Renyuan Xi, and Huining Yang, 'Recent Advances in Reinforcement Learning in Finance' (2023) 33(3) Mathematical Finance 437 <https://doi.org/10.1111/mafi.12382> accessed 17 July 2024. The authors provide for an overview of recent developments in the field of RL in finance, discussing several application domains.

196 Shuo Sun, Rundong Wang, and Bo An, 'Reinforcement Learning for Quantitative Trading' (2023) 14(3) ACM Transactions on Intelligent Systems and Technology, Article 44, 2 <https://doi.org/10.1145/3582560> accessed 17 July 2024.

197 *E.g.*, Fischer (n 194) 2; Sun, Wang, and An (n 196) 21, which highlight the limitations of the existing literature due to simulations that often do not adequately reflect the impact of RL agents' trading actions on other market participants.

198 *E.g.*, Sun, Wang, and An (n 196) 6.

mathematical problem with investors' long-term goals.[199] RL has also demonstrated promising results in the field of HFT, improving performance in tasks such as predicting directional price movements from order book signals, trade execution, and smart order routing.[200]

In sum, RL defines a highly heterogeneous category of computational approaches inspired by the way human knowledge develops through cognitive experience and interactions with the living environment.[201] RL shares similarities with how human traders traditionally operate in financial markets, learning from their experiences and strategies to pursue their profit-maximising goals (i.e. through successes and failures).[202] As we shall see, RL serves as a fundamental paradigm for establishing end-to-end ML approaches, such as autonomous trading agents. However, before delving further into this area, we will introduce the latest generation of AI methods for financial trading, referred to as 'Deep Computational Finance'.

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199 *See* Fischer (n 194) 2; Vangelis Bacoyannis and others, 'Idiosyncrasies and challenges of data driven learning in electronic trading' in *Proceedings of NIPS 2018 Workshop on Challenges and Opportunities for AI in Financial Services: The Impact of Fairness, Explainability, Accuracy, and Privacy, Montréal, Canada* (NIPS 2018) <https://arxiv.org/abs/1811.09549> accessed 17 July 2024; *see also* Sun, Wang, and An (n 196) 6.

200 For a seminal research paper on the application of RL methods to HFT-related tasks, see Michael Kearns and Yuriy Nevmyvaka, 'Machine Learning for Market Microstructure and High Frequency Trading' in David Easley, Marcos Lopez de Prado, and Maureen O'Hara (eds), *High-Frequency Trading. New Realities for Traders, Markets and Regulators* (Risk Books 2013) 91-124; *see also* Ben, Xi, and Yang (n 195) 473-74 and 483-85.

201 *See* Russell and Norvig (n 14) 840-842.

202 *See* Dennis Eilers and others, 'Intelligent Trading of Seasonal Effects: A Decision Support Algorithm Based on Reinforcement Learning' (2014) 64 Decision Support Systems 100, 102 <https://doi.org/10.1016/j.dss.2014.04.011> accessed 17 July 2024.

2.4 The Latest Generation: i.e. 'Deep Computational Finance'

In more recent years, the emergence of 'Deep Learning' (DL) methods[203] has sparked considerable enthusiasm and interest in the field of AI applications in finance.[204] Among the array of innovative ML methods—such as Generative Adversarial Networks (GANs), Transfer Learning, and Transformer architectures, to name a few[205]—DL forms the foundation of what this dissertation defines as 'Deep Computational Finance', the most cutting-edge research and practical applications in the field of ML applied to financial trading.

DL has indeed breathed new life into the ML research, demonstrating tremendous promise across various application domains such as audio, image, and video data classification, as well as in the domain of financial trading.[206] The integration of DL with other ML techniques in financial trading has led to a surge in published research, demonstrating remarkable potential in enhancing predictive modelling, pattern recognition, and decision-making processes.[207] Despite certain lingering

[203] For a comprehensive introduction to DL methods and their technicalities, see Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, 'Deep Learning' (2015) 521 Nature 436 <https://doi.org/10.1038/nature14539> accessed 17 July 2024. The article covers various aspects of DL, including the combination with SL, backpropagation, convolutional neural networks, and distributed representation and language processing. It provides a valuable overview of the fundamental concepts and techniques employed in DL, making it a useful reference for understanding the intricacies of this field.

[204] *E.g.*, William Magnuson, 'Artificial Financial Intelligence' (2020) 10 Harvard Business Law Review 337, 344 (2020) <https://scholarship.law.tamu.edu/facscholar/1435> accessed 17 July 2024; A Murat Ozbayoglu, M Ugur Gudelek, and Omer Berat Sezer, 'Deep Learning for Financial Applications: A Survey' (2020) 93 Applied Soft Computing, Article 106384, 31-36 <https://doi.org/10.1016/j.asoc.2020.106384> accessed 17 July 2024, providing a snapshot of the growing scientific literature on DL applications in finance; Cao (n 152) 20-22, who overviews a number of DL applications in the field of financial modelling.

[205] *See* footnote n. 165.

[206] *See generally* Ozbayoglu, Gudelek, and Sezer (n 204) 4-9.

[207] For a comprehensive review of emerging use cases in the financial trading domain, see Kennly Olorunnimbe and Herna Viktor, 'Deep Learning in the Stock Market—A Systemic Survey of Practice, Backtesting, and Applications' (2023) 56(3) Artificial Intelligence Review 2057 <https://doi.org/10.1007/s10462-022-10226-0> accessed 17 July 2024.

questions surrounding the validity of specific applications, DL methods empower humans to develop increasingly capable and powerful algorithmic trading systems, ultimately culminating in the creation of fully autonomous artificial trading agents. [208] In the following, we delve deeper into the subject of DL in the context of financial trading, examining both the opportunities and challenges.

A. Deep Learning

DL methods are computational approaches that structure algorithms into layers, forming 'artificial neural networks' (ANNs)—i.e. computational models that by and large draw inspiration from the structure and functioning of the human cortex. ANNs employ multiple levels of abstraction, including so-called 'hidden layers' in 'convolutional neural networks' (CNNs)[209], to analyse input data and extract meaningful patterns.[210] In DL, the ANN architecture determines the organisation of a given system. Inputs to the network are determined by the training data, while the output is generally a function of the expected output. The design of the layers between input and output is a decision influenced by the network architecture, which is based on multiple connections. There exists a vast and rapidly evolving number of ANN architectures that can be employed in various domains.[211]

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[208] *See, e.g.*, Ngoc Duy Nguyen, Thanh Nguyen, and Saeid Nahavandi, 'System Design Perspective for Human-Level Agents Using Deep Reinforcement Learning: A Survey' (2017) 5 IEEE Access 27091 <https://doi.org/10.1109/ACCESS.2017.2777827> accessed 17 July 2024.

[209] For an introduction to CNN architectures, see Laith Alzubaidi and others, 'Review of Deep Learning: Concepts, CNN Architectures, Challenges, Applications, Future Directions' (2021) 8 Journal of Big Data, Article 53 <https://doi.org/10.1186/s40537-021-00444-8> accessed 17 July 2024; *see also* Ozbayoglu, Gudelek, and Sezer (n 204) 5, for a discussion of CNN applications in the financial trading domain.

[210] *See, e.g.*, Li Deng and Dong Yu, 'Deep Learning: Methods and Applications' (2014) 7(3-4) Foundations and Trends in Signal Processing 197, 224 <http://dx.doi.org/10.1561/2000000039> accessed 17 July 2024; *see also* Russell and Norvig (n 14) 801-839.

[211] *See* Olorunnimbe and Viktor (n 207) 2072-2084, providing an examination of the most popular ANN frameworks employed in financial trading.

Despite the need for high computational power, one key advantage of DL methods over traditional linear statistical approaches is their ability to learn non-linear functions, allowing for the identification of latent patterns in the data that may otherwise remain elusive.[212] Moreover, the use of DL allows the flourishing of innovative approaches to support decision-making in financial trading. One interesting developments, for instance, is the employment of DL in computer vision for accurate time-series classification to enhance trading decisions.[213] Nonetheless, it is important to note that the mentioned benefits also come with inherent drawbacks, as discussed below.

First, these methods are susceptible to overfitting.[214] When a model over-fits, it has learnt a function that is excessively tailored to the training data, potentially compromising its performance when faced with new, unseen observations and their underlying statistical properties.[215] Additionally—as a more general issue in ML—, DL methods heavily rely on the quantity and quality of data. In fact, biases present in the data, such as statistically insignificant training data or other human-induced biases stemming from the model's underlying assumptions, can impact the validity of DL

[212] For some studies showing the superiority of DL methods over linear models in financial asset pricing, see Shihao Gu, Bryan Kelly, and Dacheng Xiu, 'Empirical Asset Pricing via Machine Learning' (2020) 33(5) The Review of Financial Studies 2223 <https://doi.org/10.1093/rfs/hhaa009> accessed 17 July 2024; Darwin Choi, Jiang Wenxi, and Zhang Chao, 'Alpha Go Everywhere: Machine Learning and International Stock Returns' (2020) SSRN preprint 1 <https://ssrn.com/abstract=3489679> accessed 17 July 2024.

[213] *See* Naftali Cohen, Tucker Balch, and Manuela Veloso, 'Trading via Image Classification' in *ICAIF '20: Proceedings of the First ACM International Conference on AI in Finance, October 2020* (ACM 2021) Article 53 <https://doi.org/10.1145/3383455.3422544> accessed 17 July 2024.

[214] For a discussion of the problem of overfitting in DL methods, see Shaeke Salman and Xiuwen Liu, 'Overfitting Mechanism and Avoidance in Deep Neural Networks' (2019) arXiv preprint 1, <https://arxiv.org/pdf/1901.06566.pdf> accessed 17 July 2024.

[215] For a technical account on how to deal with issues of overfitting in financial ML, see Lopez de Prado (n 161) 151-156, who highlights the fundamental role of back-testing techniques in preventing overfitting and emphasises the importance of human experts' understanding of data features in developing effective models.

outcomes.[216] Moreover, of particular concern is the black box nature of DL-powered AI systems, whereby the inner workings of the algorithm are not transparent to human stakeholders. This opacity hinders a comprehensive understanding of the underlying data processing method. And it poses challenges when assessing the validity of the output.[217] This issue will be explored in greater detail later in this chapter, as it pertains to the critical challenges associated with comprehending and explaining the decision-making process of the most-advanced AI trading algorithms.

B. Deep Reinforcement Learning and autonomous trading agents

The combination of 'Deep' *and* 'Reinforcement Learning' gives rise to a powerful approach known as 'Deep Reinforcement Learning' (DRL). DRL methods harness the upsides of both ML paradigms, allowing for (i) the processing of large datasets, (ii) identification of latent correlations by way of DL, and (iii) the ability to learn best actions to optimise a function using RL in pursuit of a pre-defined goal.[218] However, defining a precise objective function for optimisation within a specific domain and task can pose challenges in DRL-related mathematical problem.[219]

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[216] *See, e.g.*, Anirudh Goyal and Yoshua Bengio, 'Inductive Biases for Deep Learning of Higher-Level Cognition' (2020) arXiv preprint 1 <https://arxiv.org/abs/2011.15091> accessed 17 July 2024. The research study investigates the role of different inductive biases in guiding the learning process of DL methods to prioritise solutions according to certain properties.

[217] For a concise explanation of the black box problem in AI-supported decision-making, see generally Dino Pedreschi and others, 'Meaningful Explanations of Black Box AI Decision Systems' in *Proceedings of the The Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19), Honolulu, Hawaii, USA* (AAAI Press 2019) 9780-9784 <https://doi.org/10.1609/aaai.v33i01.33019780> accessed 17 July 2024. The paper examines the ethical perspective of the 'black box' problem and explores both the technical challenges and potential solutions to achieve meaningful explainability in opaque ML systems. *See also* Carlos Zednik, 'Solving the Black Box Problem: A Normative Framework for Explainable Artificial Intelligence' (2021) 34 Philosophy & Technology 265 <https://doi.org/10.1007/s13347-019-00382-7> accessed 17 July 2024.

[218] For a first introduction to DRL algorithms, see Kai Arulkumaran and others, 'A Brief Survey of Deep Reinforcement Learning' (2017) 34(6) IEEE Signal Processing Magazine 26 <https://doi.org/10.1109/MSP.2017.2743240> accessed 17 July 2024. The study provides an overview of various DRL algorithms, discussing their applications, challenges, and potential future directions in the field.

[219] *Cf.* Robert Kirk and others, 'A Survey of Generalisation in Deep Reinforcement Learning' (2022) arXiv preprint 1 <https://arxiv.org/pdf/2111.09794.pdf> accessed 17 July 2024. The authors discuss

DRL-based autonomous agents have garnered tremendous popularity for their supra-human capabilities in various real-life applications, including video[220] and board games,[221] as well as other domains such as Robotics.[222] It is noteworthy that solving such strategic problems involves a great deal of training and a lot of computational power for a DRL agent to master its large action space[223]. Consequently, applying DRL to concrete use cases in more complex environments, such as financial trading, can be quite a challenging task. Indeed, the stochastic properties of financial markets, with numerous interacting actors and their diverse behaviours, results in an overwhelmingly large action space for artificial trading agents to model. As the size of variables under observation increases—i.e. the number of assets to hold and trade and all types of related data—, the complexity of algorithms in terms of time and memory becomes inefficient.[224] Therefore, computational feasibility poses a significant challenge for the

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the challenges associated with the generalisation problem in DRL, emphasising the need for careful customisation of DRL models to specific application domains. They also address considerations related to data availability, data quality, and computational burden that impact the performance and generalisability of DRL algorithms.

220 For a ground-breaking research study on DRL agents, see Volodymyr Mnih and others, 'Human-Level Control Through Deep Reinforcement Learning' (2015) 518 Nature 529, 529-530 <https://doi.org/10.1038/nature14236> accessed 17 July 2024. The authors present the development of a deep Q-network (DQN) algorithmic agent capable of achieving human-level performance in a diverse set of forty-nine Atari 2600 games. The agent learned directly from the raw pixel inputs and game scores, demonstrating its ability to surpass professional human gamers in various gaming tasks.

221 *See* David Silver and others, 'Mastering the Game of Go with Deep Neural Networks and Tree Search' (2016) 529 Nature 484 <https://doi.org/10.1038/nature16961> accessed 17 July 2024. The authors describe the development of DRL agents capable of defeating a human professional player in the challenging and complex game of Go. The agents were trained using a unique combination of SL from human expert games and RL from simulated games. This achievement marked a significant milestone in the application of DRL to complex strategy games.

222 For a comprehensive overview of various DRL methods and their successful applications in real-life applications, see Arulkumaran and others (n 218). The authors present a thorough survey of the field of RL, including an examination of deep-Q networks, trust region policy optimisation, and asynchronous advantage actor-critic algorithms.

223 In RL-based methods, the 'action space' represents the set of possible actions that an agent can take to achieve a desired goal within a given environment, starting from an initial configuration. For a comprehensive discussion on different RL methods applied to financial trading, particularly from the perspective of the action space, see Fischer (n 194).

224 *See, e.g.*, Hongyang Yang and others, 'Deep Reinforcement Learning for Automated Stock Trading: An Ensemble Strategy' in *ICAIF '20: Proceedings of the First ACM International Conference on AI in Finance, October 2020* (ACM 2021) Article 31, 4

reliable application of DRL agents due to the potentially infinite action space they may face in real market settings.[225] Despite this technical limitation, however, DRL methods are very promising approaches, as they can help create increasingly autonomous and high-performance artificial trading agents, potentially excluding human control as a last resort.[226]

In principle, a DRL-based trading agent can benefit from the synergies of DL and RL combined in a single system. Existing research in Computational Finance provides at least preliminary evidence of the advantages offered by DRL applications in algorithmic trading.[227] For instance, a DRL agent can first leverage DL to extract meaningful trading signals, by analysing market data and technical indicators, from a dynamic and complex market environment. Then, on this basis, it can employ an RL algorithm to identify the best trading policy by interacting with markets and evaluating its trading performance.[228]

<https://dl.acm.org/doi/10.1145/3383455.3422540> accessed 17 July 2024; Jan-Alexander Posth and others, 'The Applicability of Self-Play Algorithms to Trading and Forecasting Financial Markets' (2021) 4 Frontiers in Artificial Intelligence, Article 668465 <https://doi.org/10.3389/frai.2021.668465> accessed 17 July 2024.

225 Yang and others (n 224) 4.

226 *Cf., e.g.*, Shavandi and Khedmati (n 168) 1; *but see* Sri Utami Ady and others, 'Trading Robots: Effective but Limited in Replacing Human Traders for Short-Term Investors' in Hyeyun Ku and others (eds), *Proceedings of the International Conference on Advance Research in Social and Economic Science (ICARSE 2022)* (Atlantis Press 2023) 254 <https://doi.org/10.2991/978-2-38476-048-0_28> accessed 17 July 2024, noting that "*[t]rading robots and automation will be employed more and more in the future, but it is important to keep in mind how clever a trading robot is, it cannot take the position of humans because it must be programmed by humans*".

227 *See, e.g.*, Zihao Zhang, Stefan Zohren, and Stephen Roberts, 'Deep Reinforcement Learning for Trading' (2020) The Journal of Financial Data Science 25 <https://doi.org/10.3905/jfds.2020.1.030> accessed 17 July 2024. The paper focuses on the development of a DRL algorithmic agent that is specifically designed to derive trading strategies for continuous future contracts. *But see* Tidor-Vlad Pricope, 'Deep Reinforcement Learning in Quantitative Algorithmic Trading: A Review' (2021) arXiv preprint 1 <https://arxiv.org/abs/2106.00123> accessed 17 July 2024, offering insights and analysis on the challenges and limitations of utilising DRL in the trading domain.

228 *See, e.g.*, Yue Deng and others, 'Deep Direct Reinforcement Learning for Financial Signal Representation and Trading' (2017) 28 IEEE Transactions on Neural Networks and Learning Systems 653 <https://doi.org/10.1109/TNNLS.2016.2522401> accessed 17 July 2024, which explore the training of ML-based trading systems using a recurrent deep neural network to process real-time financial signals and make trading decisions; Yang Li, Wanshang Zheng, and Zibin Zheng, 'Deep

It is worth reiterating, however, that the computational complexity faced by a DRL agent to efficiently explore the action space and operate safely in a given market environment is necessarily context-specific.[229] The level of model complexity and computational power needed for optimising a single task (e.g., trade execution related to a single asset in a single market), largely differs from that required when operating across multiple venues and trading multiple assets concurrently (e.g., in statistical arbitrage strategies). In the latter scenario, indeed, the agent needs to monitor, simultaneously, a larger number of variables or features; hence, its action scope is substantially broader.[230]

Moreover, it is crucial to recognise that DRL is just one approach among many to achieve higher levels of autonomy and sophistication in algorithmic trading. Unlike the standalone ML paradigms mentioned earlier, it should be clarified that the most innovative and promising algorithmic trading systems employed by financial institutions often integrate multiple ML components.[231] As a matter of fact, contemporary trading systems should be viewed as complex ecosystems of algorithms,

Robust Reinforcement Learning for Practical Algorithmic Trading' (2019) 7 IEEE Access 108014 <https://ieeexplore.ieee.org/document/8786132> accessed 17 July 2024, presenting a DRL-based trading agent able to deal with feature extraction and trading strategy design tasks in real trading environments such as stock and futures markets.

229 *See, e.g.*, Adrian Millea, 'Deep Reinforcement Learning for Trading – Critical Survey' (2021) 6(11) Data 119 <https://www.mdpi.com/2306-5729/6/11/119> accessed 17 July 2024.

230 *See* footnotes n. 224 and 225 and accompanying text. However, it is worth noting that the employment of more complex methods and architectures may help limiting some of these challenges. For an innovative proposal, see Adriano Koshiyama and others, 'QuantNet: Transferring Learning Across Trading Strategies' (2021) 22(6) Quantitative Finance 1071 <https://doi.org/10.1080/14697688.2021.1999487> accessed 17 July 2024. The authors propose a Transformer architecture that combines advanced Transfer and Meta-learning methods to achieve a global trading strategy based on an end-to-end learning system. The proposed architecture is able to learn systemic, market-agnostic trends and apply these to learn superior market-specific strategies by transferring knowledge among single strategies.

231 *See generally* Koshiyama, Firoozye, and Treleaven (n 165).

which require some level of human involvement in order to ensure, for instance, accurate, reproducible, reliable, predictable, and explainable results.[232]

Different ML methods and algorithms can be combined into complex architectures, such as integrated or hybrid systems, or ensemble strategies. In the case of DRL, various ML components can be integrated into ensemble strategies, which leverage the advantages of different algorithms.[233] Certain ensemble strategy can also involve the combination of different types of trading approaches such as pure quantitative trading and sentiment analysis.[234] Additionally, the architecture on which to build DRL agents can show different levels of sophistications.[235] Furthermore, multiple ML-based agents can be combined within multi-agent systems[236], leveraging their specialised skills through collaborative or competitive approaches,[237] and also

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[232] *See* ibid; Mihov, Firoozye, and Treleaven (n 53); *see also* Kristian Bondo Hansen, 'The Virtue of Simplicity: On Machine Learning Models in Algorithmic Trading' (2020) 7(1) Big Data & Society 1 <https://doi.org/10.1177/2053951720926558> accessed 17 July 2024.

[233] *See, e.g.*, Yang and others (n 224), which trained a DRL agent and obtained an ensemble strategy based on three actor-critic based algorithms; Kong and So (n 188), which developed an ensemble strategy based on several actor-critic algorithms.

[234] *See, e.g.*, Akhil Raj Azhikodan, Anvitha GK Bhat, and Mamatha V Jadhav, 'Stock Trading Bot Using Deep Reinforcement Learning' in Harvinder Singh Saini and others (eds), *Innovations in Computer Science and Engineering: Proceedings of the Fifth ICICSE 2017* (Springer Cham 2019) 41-49 <https://doi.org/10.1007/978-981-10-8201-6_5> accessed 17 July 2024.

[235] *See, e.g.*, Bing Yang and others, 'Deep Reinforcement Learning Based on Transformer and U-Net Framework for Stock Trading' (2023) 262 Knowledge-Based Systems, Article 110211 <https://doi.org/10.1016/j.knosys.2022.110211> accessed 17 July 2024, which combine an end-to-end DRL model with Transformer layers and a U-Net architecture. The Transformer layers are employed to capture complex and dynamic patterns in financial markets data, while the U-Net architecture that contains multiple skip connections allows the model to combine long- and short-term features. As an output, the model generates (i) trading actions and (ii) action weights, allowing the agent to balance between buying and selling, thus better managing investment risk.

[236] For a theoretical introduction to multi-agent systems from a Systems Engineering perspective, see Manuela Herrera and others, 'Multi-Agent Systems and Complex Networks: Review and Applications in Systems Engineering' (2020) 8 Processes, Article 312 <http://dx.doi.org/10.3390/pr8030312> accessed 17 July 2024.

[237] *See, e.g.*, Salvatore Carta and others, 'A Multi-Layer and Multi-Ensemble Stock Trader Using Deep Learning and Deep Reinforcement Learning' (2021) 51 Applied Intelligence 889, 889-905 <https://doi.org/10.1007/s10489-020-01839-5> accessed 17 July 2024. The authors develop a multi-layer and multi-ensemble stock trading agent thanks to the combination of DL and RL methods in a unique strategy to trade on futures markets; Shavandi and Khedmati (n 168).

integrate ensemble strategies to achieve optimal performance.[238] Nevertheless, due to ML, the increasing complexity of AI trading architectures and systems presents significant challenges from a Software Engineering perspective, both during the development and subsequent phases of a given project.[239] As will be argued, this additional source of complexity raises several questions on how to ensure effective governance and regulation of AI-powered technology in financial trading.

Overall, based on a rigorous review of existing research in the field of (Deep) Computational Finance, DRL methods emerge as the primary and most innovative ML frameworks for implementing increasingly capable and autonomous AI trading agents. As we shall see, however, while these technological advancements have a number of advantages, it is essential to carefully consider the risks associated with the use of highly sophisticated trading systems, which necessitate deeper scrutiny and analysis.

2.5 The Additional Risks Associated with ML-Powered Trading

The effective governance of advanced AI trading systems based on ML faces numerous uncertainties, primarily due to their technical intricacies. Like other areas in ML research, the field of 'Deep Computational Finance' integrates interdisciplinary scientific knowledge and methods that go beyond the mere advancement of financial

[238] *See* Cavalcante and others (n 177) 204-205; For a concrete example of possible application, see Salvatore Carta and others, 'Multi-DQN: An Ensemble of Deep Q-learning Agents for Stock Market Forecasting' (2021) 164 Expert Systems with Applications, Article 113820 <https://doi.org/10.1016/j.eswa.2020.113820> accessed 17 July 2024. The authors propose a ML ensemble model that combines various DRL algorithms. By leveraging different experiences on market dynamics, these agents engage in cooperative tasks and employ competing strategies to determine the best policy actions.

[239] *See, e.g.*, Saleema Amershi and others, 'Software Engineering for Machine Learning: A Case Study' in *ICSE-SEIP '19: Proceedings of the 41st International Conference on Software Engineering: Software Engineering in Practice* (IEEE 2019) 291-300 <https://ieeexplore.ieee.org/document/8804457> accessed 17 July 2024, highlighting differences in terms of greater complexity in (i) data discovery, managing, and versioning, (ii) model customisation and re-use, and (iii) handling of AI components; Imane Bakkar and others, 'Software Validation and Artificial Intelligence – A Primer' (October 2021) Bank of England, Staff Working Paper No. 947 <https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2021/software-validation-and-artificial-intelligence-in-finance-a-primer.pdf> accessed 17 July 2024.

practice.[240] Owing to the complex nature of AI trading—both in terms of AI components, systems, architectures, and infrastructures—which rests on a combination of emerging and rapidly evolving technologies, market actors face substantial challenges in ensuring trustworthy adoption.[241] Indeed, the safe and reliable development, training, validation, testing, implementation, use, deployment, and maintenance of algorithmic trading systems require an engineering approach to complexity mastering,[242] within the context of the 'AI lifecycle'[243].

In order to gain a deeper understanding of the additional system complexity introduced by AI in capital markets, it is fundamental to examine the key challenges associated with techno-methodical aspects of ML. The aspects include, for instance, the construction of models, the handling of datasets, the selection of features, the tuning of parameters and hyperparameters, the definition of loss function, among others. Each of these components, in fact, presents practical challenges that need to be addressed for the effective, safe, and responsible use of AI tools. Additionally, it is crucial to explore the ethical and legal implications associated with the use of

240 *Cf.* footnotes n. 108, 116, 117, and 206 and accompanying text.

241 *See* Kelvin Lui and Jeff Karmiol, 'AI Infrastructure Reference Architecture' (June 2018) IBM Systems, 87016787USEN-00 <https://www.ibm.com/downloads/cas/W1JQBNJV> accessed 17 July 2024; BoE and FCA, 'Artificial Intelligence Public-Private Forum: Final Report' (February 2022) 15-17 (concerning complexity in data structures) and 21-27 (on model complexity) <https://www.bankofengland.co.uk/-/media/boe/files/fintech/ai-public-private-forum-final-report.pdf> accessed 17 July 2024 [hereinafter BoE and FCA III]; AFM (n 105) 20-24; *see also* ESMA (n 129) 4.

242 *See, e.g.*, Bakkar and others (n 239); Mark Haakman and others, 'AI Lifecycle Models Need to Be Revised' (2021) 26 Empirical Software Engineering 95 <https://doi.org/10.1007/s10664-021-09993-1> accessed 17 July 2024. The authors argue that, within the FinTech industry, the ML research has until now failed to address the challenges inherent to the ML lifecycle.

243 With the term AI lifecycle, we usually refer to all the stages involved in the development, deployment, use, and management of AI systems. It therefore encompasses the entire AI process, from the initial conception of a given AI project to its ongoing maintenance and subsequent improvement. Each and every stage in the AI lifecycle is crucial for ensuring the effectiveness, reliability, ethical, and legally compliant use of AI systems. *See, e.g.*, Daswin De Silva and Damminda Alahakoon, 'An Artificial Intelligence Life Cycle: From Conception to Production' (2022) 3(6) Patterns, Article 100489 <https://doi.org/10.1016/j.patter.2022.100489> accessed 17 July 2024.

increasingly powerful yet sophisticated ML methods, particularly those based on DL—such as the deployment of DRL trading agents.

A. The main techno-methodical challenges in ML

As a result of growing technological sophistication, contemporary AI trading system means bear little resemblance to traditional trading desks: they looks more like experimental laboratories or industrial production lines.[244] In fact, the operationalisation of these systems requires treating the training of ML models as an actual experiment, in which the ability both to evaluate system performance, ensure explainability, control system behaviour is crucial to achieving trustworthy applications.[245] In this context, innovative ML applications in financial trading—such as DRL agents—pose various techno-methodical challenges, not only in terms of achieving successful results but also in ensuring regulatory compliance for organisations using these technologies.[246]

One significant challenge pertains to the critical role of data. Data have always played a vital role in financial forecasting and decision-making under uncertainty. In the context of capital markets, data collection and analysis assist humans in deriving meaningful insights to better comprehend the domain of financial markets and support financial decision-making, such as identifying profitable trading opportunities.[247] As data-driven approaches to empirical discovery, ML methods offer innovative tools to

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244 *See* footnotes n. 241-242.

245 Remy Kusters and others, 'Interdisciplinary Research in Artificial Intelligence: Challenges and Opportunities' (2020) 3 Frontiers in Big Data, Article 577974 <https://www.frontiersin.org/articles/10.3389/fdata.2020.577974> accessed 17 July 2024.

246 *E.g.*, FSB (n 132) 28; Bacoyannis and others (n 199) 6; OECD (n 135) 51; and IOSCO (n 135) 9-13.

247 For a chronicle of financial econometrics techniques, see Tim Bollerslev, 'Financial Econometrics: Past Developments and Future Challenges' (2001) 100 Journal of Econometrics 41 <https://doi.org/10.1016/S0304-4076(00)00052-X> accessed 17 July 2024.

address uncertainty in finance.[248] Nevertheless, the performance of these methods heavily relies on the quality and accessibility of training data. Training an ML algorithm necessitates the availability of high-quality data, which may be collected and enhanced from multiple sources.[249] To ensure that training data are of utmost quality, human experts must take necessary measures to safeguard statistical representativeness and mitigate bias. In addition, data scientists must take reasonable steps to handle data inconsistencies, such as irregular or invalid input data, which can adversely affect any learning method.[250] When data are insufficient in volume, they can be augmented by synthetic data generation.[251] However, the feasibility of this approach depends on the quality of data being replicated, which must reflect the realistic behaviour of financial markets and be supported by sound statistical modelling.[252] For this reason, not only

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248 *See generally* Cris Doloc, *Computational Intelligence in Data-Driven Trading* (Wiley 2019) 15-35. The book delves into various aspects of applying computational intelligence techniques to trading, offering discussions on topics such as data analysis, algorithmic trading strategies, and risk management. *But see* Hansen Kristian Bondo and Christian Borch, 'The Absorption and Multiplication of Uncertainty in Machine-Learning Driven Finance' (2021) 72(4) The British Journal of Sociology 1015 <https://doi.org/10.1111/1468-4446.12880> accessed 17 July 2024. The authors argue that the use of ML methods introduces a new form of uncertainty for capital markets, specifically 'model uncertainty'.

249 *See, e.g.*, DELL Technologies and NVIDIA, 'Algorithmic Trading: HPC & AI Reference Guide' (2020) 31-36 <https://www.delltechnologies.com/asset/en-sg/products/ready-solutions/industry-market/hpc-ai-algorithmic-trading-guide.pdf> accessed 17 July 2024; BoE and FCA III (n 241) 17-18.

250 *See, e.g.*, OECD (n 135) 37-38.

251 For an in-depth research study of various data augmentation techniques that discusses their possible application in finance and their limitations, see Jonathan Kinlay, 'Synthetic Market Data and its Applications' (2023) SSRN preprint 1 <https://ssrn.com/abstract=4380552> accessed 17 July 2024. For examples on the application of synthetic data to train DRL methods, see Chunli Liu, Carmine Ventre, and Maria Polukarov, 'Synthetic Data Augmentation for Deep Reinforcement Learning in Financial Trading' in Daniele Magazzeni and others (eds), *ICAIF '22: Proceedings of the Third ACM International Conference on AI in Finance* (ACM 2022) 343-351 <https://doi.org/10.1145/3533271.3561704> accessed 17 July 2024; Alessio Brini and Daniele Tantari, 'Deep Reinforcement Trading with Predictable Returns' (2023) 622 Physica A, Article 128901, 2 <https://doi.org/10.1016/j.physa.2023.128901> accessed 17 July 2024.

252 *See* Ali Hirsa and others, 'Deep Reinforcement Learning on a Multi-Asset Environment for Trading' (2021) arXiv preprint 1, 10 <https://doi.org/10.48550/arXiv.2106.08437> accessed 17 July 2024, who apply data augmentation techniques to train a DRL trading agent; *see also* Golshild Ranjbaran and others, 'Leveraging Augmentation Techniques for Tasks with Unbalancedness within the Financial Domain: A Two-Level Ensemble Approach' (2023) 12 EPJ Data Science, Article 24 <https://doi.org/10.1140/epjds/s13688-023-00402-9> accessed 17 July 2024, discussing various data augmentation techniques in the context of several financial applications.

appropriate mathematical models are needed to validate generative models of synthetic financial data, but the latter should also be subject to post-generation validation.[253]

More generally, ML methods applied to financial trading must address the mathematical challenge of dealing with the non-deterministic behavioural properties of capital markets, which are notoriously difficult to model. Indeed, the noisy, non-stationary, and sometimes unpredictable nature of financial markets complicates the task of modelling market dynamics, even for sophisticated ML approaches such as DRL-based agents.[254] For instance, to achieve their goals effectively through an optimal sequence of actions, DRL agents must not only explore the entire action space, partially defined by the flow and evolution of empirical data, but also consider the effects of their trading strategy and other market constraints.[255] Cumulatively, these factors can lead to computational limitations in terms of time and memory, particularly when dealing with high-dimensional spatio-temporal data.[256]

To overcome some of these technical limitations, we have previously examined how DRL agents can exploit the potential offered by the synergic integration of RL with DL methods.[257] However, reliance on DL methods can also make trading agents more susceptible to overfitting and model selection issues. Both these issues highlight the importance of model validation tasks, such as back-testing[258], in ensuring that a given

[253] *See* Valerie Marshall and others, 'Exploring Synthetic Data Validation – Privacy, Utility and Fidelity' (2023) FCA Research Paper <https://www.fca.org.uk/publications/research-articles/exploring-synthetic-data-validation-privacy-utility-fidelity> accessed 17 July 2024.

[254] *See, e.g.*, Bacoyannis and others (n 199) 2-3; Chien-Yi Huang, 'Financial Trading as a Game' (2018) arXiv preprint 1, 3 <https://arxiv.org/abs/1807.02787> accessed 17 July 2024; Zejnullahu, Moser, and Osterrieder (n 191) 3.

[255] Bacoyannis and others (n 199) 4; Huang (n 254) 3; Zejnullahu, Moser, and Osterrieder (n 191) 3.

[256] Bacoyannis and others (n 199) 5-6; *see also* footnote n. 224.

[257] *But see* Kirk and others (n 219).

[258] In computational finance, back-testing refers to the methods used to evaluate the performance of a predictive model or a trading strategy by applying it to historical data. It enables human experts to

model can effectively fulfil its intended purpose.[259] Additionally, as discussed further below, DL-based approaches to financial trading may often invoke black box problems, creating uncertainties regarding safe and reliable applications. This, in turn, opens up to various ethical and legal concerns and casts doubts on the effectiveness of existing governance and regulatory frameworks. All these issues need to be adeptly addressed to ensure the integration of these innovative technologies into the financial industry. Indeed, as history has shown, the use of automated technology and data analytics without a sound scientific methodology and ethical considerations can lead to unintended consequences and even harm to markets and society as a whole.[260]

B. Black box trading and ethical-legal dilemmas

The use of black box algorithmic trading systems raises significant ethical and legal concerns. Particularly, financial institutions that employ AI trading tools are responsible to ensure their compliance with regulatory requirements, including market conduct rules. It is therefore crucial for these firms to engage in fair and permissible activities and exercise due care in managing their algorithmic systems to prevent potential market disruptions.[261] By actively addressing issues of opacity, financial institutions can foster trust and maintain a responsible approach to ML-powered algorithmic trading.

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analyse how the strategy would have performed if it had been employed in the past. By simulating trades and comparing the strategy's predictions against actual historical data, back-testing provides valuable insights into the effectiveness and potential limitations of the model or strategy. *See* Lopez de Prado (n 161) 151-156, who provides further details and considerations related to back-testing, offering insights into its role in evaluating and refining predictive models in Computational Finance.

259 *See, e.g.*, Posth and others (n 224) 3-5; Olorunnimbe and Viktor (n 207) 2078-2081.

260 *See* Cathy O'Neil, *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (Crown 2016). The book highlights how mathematical models employed in AI system reinforce biases and discrimination, leading to unfair outcomes in areas such as education, employment, and criminal justice.

261 For an account, from an EU perspective, about the challenges and implications of opaque algorithmic trading practices as well as the legal and regulatory approaches to ensure transparency, see Spindler (n 92).

In the context of our analysis, the black box problem arises when human experts are unable to fully understand or explain *why* and *how* their trading algorithms produce specific outcomes based on given input data.[262] This lack of transparency contributes to creating an 'accountability gap', which raises concerns of human responsibility and liability for AI systems' misconduct and harm.[263] The black box problem is linked to aspects of AI transparency and explainability, which underpins the challenges to ensure safe, responsible, and trustworthy applications, especially in critical areas related to human life and fundamental rights.[264]

In principle, there can be various reasons why AI systems behave like black boxes.[265] First, opacity could be a deliberate design choice by users to keep the details of their AI trading systems secret, aiming to gain and maintain a competitive advantage.[266] Alternatively, opacity may be an unintended consequence resulting from the use of sophisticated trading systems due to a lack of specialised human expertise

[262] *See* footnote n. 217; *see also* Florian Ostmann and Cosmina Dorobantu, 'AI in Financial Services' (2021) The Alan Turing Institute, 48-63 <https://zenodo.org/record/4916041/files/ATI_AI%20in%20Financial%20Services.pdf> accessed 17 July 2024, examining various aspects of transparency relating to both AI systems and processes.

[263] *See* Brent D Mittelstadt and others, 'The Ethics of Algorithms: Mapping the Debate' (2016) 3(2) Big Data & Society 1, 11 <https://doi.org/10.1177/2053951716679679> accessed 17 July 2024, stating that "*[t]he gap between the designer's control and algorithm's behaviour creates an* accountability gap … *wherein blame can potentially be assigned to several moral agents simultaneously*"; *see also* Filippo Santoni de Sio and Giulio Mecacci, 'Four Responsibility Gaps with Artificial Intelligence: Why They Matter and How to Address Them' (2021) 34 Philosophy & Technology 1057 <https://doi.org/10.1007/s13347-021-00450-x> accessed 17 July 2024, noting however that "*discussions about "responsibility" or "accountability gaps" are sometimes partial … [and] … the focus on … "autonomous systems" may be too limited. Responsibility gaps are due to a multiplicity of factors and are sometimes only aggravated by the presence of machines that learn and act on their own*".

[264] For a survey study on the key aspects relating to AI transparency and explainability and their implication for AI adoption in critical domains such as transportation, healthcare, criminal law, and the military, see Amina Adadi and Mohammed Berrada, 'Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)' (2018) 6 IEEE Access 52138 <https://doi.org/10.1109/ACCESS.2018.2870052> accessed 17 July 2024.

[265] *See* Jenna Burrell, 'How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms' (2016) 3(1) Big Data & Society 1 <https://doi.org/10.1177/2053951715622512> accessed 17 July 2024.

[266] Ibid 3.

in their design, development, implementation, deployment, and usage.[267] Opacity may also be unavoidable in those complex ML approaches involving, for instance, DRL-based trading agents.[268]

Whereas the inner working of traditional, hence non-ML approaches to algorithmic trading is determined by human knowledge encapsulated in algorithms and data structures, ML methods enable self-learning from empirical domain data to dynamically adapt to changing situations based on new observations. Therefore, understanding, defining, and mitigating the causes of opacity in ML-powered algorithmic trading systems are all crucial elements for ensuring the acceptance of innovative AI trading solutions and strategies from both ethical, legal, and regulatory perspectives. This requirement must be observed either when firms or individuals autonomously develop—with or without reliance on open-source content—ML algorithms and systems, or when they acquire ML components or solutions from third parties.[269]

In addressing issues of opacity in AI systems, 'Explainable AI', or XAI, is indeed consolidating as a fundamental field of interdisciplinary research in ML, with an increasing number of applications also within the '(Deep) Computational Finance' community.[270] In the literature, two seemingly competing school of thoughts are emerging around the concepts of AI transparency, interpretability, and

[267] Ibid 4. *But see* Lopez de Prado (n 161) 15-16 and 113-114, who dismisses the concrete existence of the black box problem in the professional algorithmic trading context as a misplaced argument.

[268] *See* Burrell (n 265) 4-5.

[269] *See, e.g.*, FSB (n 132) 26; BoE and FCA III (n 241) 23-24; ESMA (n 129) 11.

[270] *See* Alejandro Barredo Arrieta and others, 'Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges Toward Responsible AI' (2020) 58 Information Fusion 82, 84 <https://doi.org/10.1016/j.inffus.2019.12.012> accessed 17 July 2024. The authors provide an overview of the current advancements in the XAI research. They emphasise the importance of AI explainability in ensuring effective auditability and accountability among various stakeholders involved in AI systems. The article explores concepts, taxonomies, opportunities, and challenges related to XAI, highlighting its significance for responsible AI development.

explainability.[271] On one hand, a regulatory solution could entail higher demand for transparency[272] in AI systems.[273] Some researchers and experts in the field argue in favour of model interpretability[274] as a remedy.[275] A more radical alternative would be to 'open the black box' by providing direct and transparent access to the AI decision-making process to interested stakeholders such as financial regulators and supervisors.[276] However, the application of this latter solution may face several legal and practical obstacles. In fact, opening the black box of AI systems may hinder

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271 For a discussion of the relationship between transparency, interpretability, and explainability in human-agent systems, see Avi Rosenfeld and Ariella Richardson, 'Explainability in human-agent systems' (2019) 33(3) Autonomous Agents and Multi-Agent Systems 673 <https://link.springer.com/article/10.1007/s10458-019-09408-y> accessed 17 July 2024.

272 For an account on the interplay between different dimension of transparency and trust in ML-based systems, see John Zerilli, Umang Bhatt, and Adrian Weller, 'How transparency modulates trust in artificial intelligence' (2022) 3(4) Patterns, Article 100455 <https://doi.org/10.1016/j.patter.2022.100455> accessed 17 July 2024.

273 *Cf*. Inioluwa Deborah Raji and Yang Jingying, 'ABOUT ML: Annotation and Benchmarking on Understanding and Transparency of Machine Learning Lifecycles' (2019) arXiv preprint 1 <https://arxiv.org/abs/1912.06166> accessed 17 July 2024. However, the authors note "*transparency is … the most prevalent principle in the … literature … [but] the intricacy and difficulty of translating the high-level ethical ideal of transparency into concrete engineering processes and requirements has been repeatedly referenced as a major challenge*".

274 *See* Rosenfeld and Richardson (n 271), which provide a comprehensive review of relevant literature along with a discussion on various approaches and tools for interpretability in ML; Cynthia Rudin and others, 'Interpretable Machine Learning: Fundamental Principles and 10 Grand Challenges' (2022) 16 Statistics Surveys 1 <https://doi.org/10.1214/21-SS133> accessed 17 July 2024. The authors define interpretable ML as a "*model [that] obeys a domain-specific set of constraints to allow it (or its predictions, or the data) to be more easily understood by humans.*"

275 *See* Cynthia Rudin, 'Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead' (2019) 1 Nature Machine Intelligence 206 <https://doi.org/10.1038/s42256-019-0048-x> accessed 17 July 2024; *see also* Rudin and others (n 274), discussing a number of technical challenges in interpretable ML—also in the context of RL methods.

276 For instance, had it been passed in the US, Regulation AT would have opened the source code of algorithmic traders to inspection by US Commodity Futures Trading Commission (CFTC). *See, e.g.*, Megan Woodward, 'The Need for Speed: Regulatory Approaches to High Frequency Trading in the United States and the European Union' (2017) 50(5) Vanderbilt Journal of Transnational Law 1359 <https://scholarship.law.vanderbilt.edu/vjtl/vol50/iss5/7> accessed 17 July 2024, which explores the pursuit of transparency in algorithmic trading through financial regulation in the US and the EU.

innovation and competition by forcing private organisations to disclose valuable intellectual property.[277]

As less less-intrusive approaches, instead, there are *ex-post* explainability methods, which refer to techniques employed to retrospectively understand and explain the decision-making process and outcomes of AI systems after they have generated results or predictions. These methods aim to provide insights into how AI models or processes generated specific outcomes, allowing for some level of transparency and accountability towards interested stakeholders, and potentially the identification of biases or mistakes.[278]

In sum, issues of opacity underlie the challenges inherent in the auditing, control, maintenance, and supervision of ML-based systems, raising fundamental questions regarding human accountability, responsibility, and liability.[279] As will be discussed in next chapters, these concerns assume even greater relevance whenever AI systems powered by opaque ML methods result in wrongdoing and harm to markets. For now, it suffices to say that using profitable ML-powered trading systems without a comprehensive understanding or meaningful control over their behaviour is an irresponsible practice. At the very least, it can be regarded as a distorted form of free riding. Financial institutions that employ AI trading in a negligent manner or for unfair market practices or illicit purposes externalise the costs of their risky activities onto

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277 *See, e.g.*, Hilary J Allen, 'Driverless Finance' (2020) 10 Harvard Business Law Review 157 <https://digitalcommons.wcl.american.edu/facsch_lawrev/695> accessed 17 July 2024.

278 *See generally* Sahil Verma and others, 'Counterfactual Explanations and Algorithmic Recourses for Machine Learning: A Review' (2020) arXiv preprint 1 <https://arxiv.org/abs/2010.10596> accessed 17 July 2024; *see also* Alexandre Heuillet, Fabien Couthouis, and Natalia Díaz-Rodríguez, 'Explainability in Deep Reinforcement Learning' (2021) 214 Knowledge-Based System, Article 106685 <https://doi.org/10.1016/j.knosys.2020.106685> accessed 17 July 2024, who discuss XAI methods in the context of DRL.

279 *See, e.g.*, Arrieta and others (n 270).

other market participants and undermine the informativeness of market prices.[280] Therefore, it is crucial to address the black box problem in order to ensure to preserve the quality, integrity, and stability of capital markets.

C. Reproducibility, transparency, and access to 'Deep Computational Finance' research

The field of 'Deep Computational Finance' has been experiencing rapid and continuous growth;[281] however, it still faces various methodical challenges in evaluating the performance and the validity of different ML applications.[282] One significant obstacle lies in the difficulty to conduct comparative analysis, specifically through benchmarking.[283] The lack of globally recognised standard benchmark and tools in the academic community impedes the effective comparison of various ML methods and ensemble strategies in terms of their theoretical limits, accuracy, and experimental success/failure results.[284]

With respect to the DRL research, there is not a unified and agreed-upon methodology to rank different applications. This lack of consolidation and standardisation in the field extends to the selection of baseline methods and

[280] *E.g.*, O'Neil (n 260); Pasquale (n 27); *see also* Ekaterina Svetlova, 'AI Ethics and Systemic Risks in Finance' (2022) 2 AI and Ethics 713 <https://doi.org/10.1007/s43681-021-00129-1> accessed 17 July 2024.

[281] For a systemic literature review of published work relating to various financial application domains in the period between 2011 and 2021, counting 348 scientific papers, see Shamina Ahmed and others, 'Artificial Intelligence and Machine Learning in Finance: A Bibliometric Review' (2022) 61 Research in International Business and Finance, Article 101646 <https://doi.org/10.1016/j.ribaf.2022.101646> accessed 17 July 2024. Particularly, the authors identify an upward trend in publication starting from 2015.

[282] *See generally* Spyros Makridakis, Evangelos Spiliotis, and Vassilios Assimakopoulos, 'Statistical and Machine Learning Forecasting Methods: Concerns and Ways Forward' (2018) 13(3) PlosONE, Article e0194889 <https://doi.org/10.1371/journal.pone.0194889> accessed 17 July 2024.

[283] *See* Lukas Ryll and Sebastian Seidens, 'Evaluating the Performance of Machine Learning Algorithms in Financial Market Forecasting: A Comprehensive Survey' (2019) arXiv preprint 1, 1-2 <https://arxiv.org/pdf/1906.07786.pdf> accessed 17 July 2024.

[284] *E.g.*, Ibid.

experimental datasets, often leading to arbitrary decisions made by researchers.[285] Additionally, research results often focus solely on algorithms' profitability, overlooking critical aspects like risk, explainability, and reliability.[286] This deficiency in theoretical control hinders the progress in the field, as many proposed approaches seem like "homemade recipes", making it difficult to isolate factors—such as datasets, signals, algorithms, hyperparameters, etc.—contributing to their performance.[287]

At the same time, the scarcity of insights from the financial industry poses another significant challenge. Proprietary trading details, such as the nature and role of the training data used, design choices (e.g., hyperparameters, hidden layers, loss function), and the learning process itself, are often kept confidential due to obvious commercial reasons, limiting transparency in the field. This lack of experimental transparency extends to academic research as well, where information on very sensitive components (e.g., hyper-parameters) related to the performance of DRL methods is often absent.[288]

The absence of replicable and validated results inhibits scientific reproducibility—a fundamental aspect of experimental science and related industry applications. This lack of information also hampers the overall development of the field, making it difficult for researchers to understand the current state and limit of research in Deep Computational Finance.[289] Addressing these challenges requires greater collaboration and data sharing between academia and the financial industry to advance the field responsibly and transparently.

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[285] *E.g.*, Sun, Wang, and An (n 196) 22.

[286] *E.g.*, Ibid.

[287] *E.g.*, Brini and Tantari (n 251) 2.

[288] *E.g.*, Sun, Wang, and An (n 196) 22.

[289] *E.g.*, ibid.

Another obstacle to ML research development is the limited access to public data, particularly in financial trading. Most relevant datasets are often only available through paid service, leading to a lack of common training framework for ML methods.[290] One potential solution to fill this *lacuna* could be the development of ML toolboxes that facilitate online learning based on publicly accessible and statistically significant financial data.[291] An interesting development in this direction involving the field of DRL is represented by the 'FinRL' and 'FinRL-Meta' libraries available on Github.[292] These open-source libraries developed for researchers and practitioners to explore and apply RL-based methods in financial trading. Both provides a set of pre-built tools and components that allow users to easily develop and test various RL-based algorithms within simulated yet realistic market environments and data.[293]

Furthermore, trust in ML research is hindered by insufficient efforts towards model explainability and accountability.[294] This is especially critical in high-risk domains like capital markets trading, whereby the ability to understand and explain AI systems' outcome and decision-making process is essential for the acceptance of these methods, including ensuring compliance with regulation.[295]

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290 *See* Olorunnimbe and Viktor (n 207) 2101.

291 Ibid 2102.

292 The FinRL library is available at the following link: <https://github.com/AI4Finance-LLC/FinRL-Library> accessed 17 July 2024. The FinRL-Meta library is available at the following link: <https://github.com/AI4Finance-Foundation/FinRL-Meta> accessed 17 July 2024.

293 *See* Xiao-Yang Liu and others, 'FinRL: Deep Reinforcement Learning Framework to Automate Trading in Quantitative Finance' in *ICAIF '21: Proceedings of the Second ACM International Conference on AI in Finance* (IEEE 2022) Article 1 <https://doi.org/10.1145/3490354.3494366> accessed 17 July 2024; Xiao-Yang Liu and others, 'FinRL-Meta: Market Environments and Benchmarks for Data-Driven Financial Reinforcement Learning' in Sanmi Koyejo and others (eds) *Advances in Neural Information Processing Systems 35 (NeurIPS 2022)* (Curran Associates 2023) <https://doi.org/10.48550/arXiv.2211.03107> accessed 17 July 2024.

294 *See* footnote n. 290.

295 *See, e.g.*, Sun, Wang, and An (n 196) 22; *see also* footnote n. 246

Addressing the above-mentioned methodological challenges is crucial for advancing the state-of-the-art DRL and fostering responsible and transparent ML research in finance, more broadly. Given these limitations in terms of 'scientificity', there is also a significant concern that AI technology in financial trading could advance without adequate regulatory scrutiny or academic and public review. This state of affairs is very worrisome. It marks the first instance in human history where we entrust cognitive agency and decision-making to algorithms, despite the potential inability to control their functioning and foresee their impact on society in the worst-case scenario. To mitigate this potential threat, it becomes imperative to develop and implement publicly negotiated and legally binding benchmarking concepts aligned with the state-of-the-art in ML performance and impact characterisation. Such concepts should encompass aspects such as, for instance, open data stewardship, standardisation of performance criteria and metrics, and the establishment of independent bodies for testing and approval. Without these measures, there may be concern regarding the safe and responsible evolution of AI technology in financial trading.

2.6 Conclusion

In this synoptic chapter, we have explored how the rapid advances in AI technology and its ramifications within algorithmic trading domain have resulted in profound transformations in this industry. The growing sophistication of AI tools and techniques has added additional layers of system complexity to capital markets, making it challenging to fully comprehend their functioning and behaviour. In this trend of technological innovation, most advanced ML methods—referred to as Deep Computational Finance in this dissertation—empowers industry players to research and deploy increasingly powerful trading systems, whose safe and reliable application however present a number of techno-methodical challenges.

While the adoption of ML in financial trading can bring anticipated benefits for private companies, their customers, and society as a whole, it also introduces novel risks and uncertainties related to the governance of this fast-evolving technology. As a dark side, in fact, AI trading may result in market accidents, disruptions, and destabilisation, affecting the economic interests of both private organisations and the general public. Thus, to promote beneficial innovation while mitigating technology-related risks, financial regulators must closely monitor AI-related developments and their effects on the financial industry. They also need to assess the adequacy of existing regulatory frameworks in addressing the additional risks introduced by AI. This, however, requires a comprehensive understanding of AI trading technology—including the concrete technical and methodical aspects related to specific ML methods—and related risks to design appropriate and proportional regulatory responses. With this in mind, this chapter has sought to provide a foundation to begin to understand the technical-methodological aspects underlying specific ML methods and the associated challenges to ensuring their safe and responsible adoption.

In the upcoming chapters, we will focus on the interplay between ML and market integrity, specifically examining novel risks of market abuse associated with AI trading leading. Our focus will be on DRL methods—which enable the development of artificial trading agents potentially replacing the role of human traders—and their potential to engage in market manipulation and even algorithmic forms of collusion in an increasingly autonomous manner. As will be discussed, these developments raise significant concerns about the adequacy of existing legal systems and regulatory regimes in addressing the governance of AI trading. Without proper governance and regulation, advancements in AI, particularly ML, may introduce unforeseen risks, ultimately undermining the fair and orderly functioning of markets up to posing a threat to their stability.

3. MARKET MANIPULATION BY AUTONOMOUS AI TRADING

After examining how different AI generations have impacted the organisation and operation of capital markets, this chapter takes a closer look at some of the negative aspects associated with the advancement of technology applied to financial trading. While algorithm-dominated markets offer various benefits, such as increased efficiency and liquidity, the rise of highly advanced trading systems may also bring about new risks to the operational resilience and integrity of capital markets.[296] Certain activities conducted by algorithmic trading may lead to negative externalities due to their potential to result in market disruptions and abuse, thus causing market failures. But if the markets themselves do not internalise the resulting costs, regulation becomes necessary to address the negative consequences of such activities and ensure market integrity, stability, and efficiency.[297]

As the era of ML-powered trading unfolds, novel forms of market abuse facilitated by advanced technology may emerge, thus requiring us to carefully evaluate their concrete feasibility. Therefore, our primary goal is to (i) define these emerging risks and (ii) comprehensively evaluate their likelihood to arise. As will be argued, AI trading agents may be capable of engaging in various forms of market manipulation in an increasingly autonomous way.

We begin this chapter by emphasising the important regulatory goal of market integrity, the safeguard of which not only upholds the efficiency of capital markets but also nurtures trust among market participants (Chapter 3.1). Next, we delve into the challenges posed by algorithmic trading for financial regulators in combating market

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[296] *See* footnotes n. 66-71 and accompanying text.

[297] *Cf.* Emilios Avgouleas, *The Mechanics and Regulation of Market Abuse: A Legal and Economic Analysis* (Oxford University Press 2005) 159 and 167-168.

abuse, describing four basic scenarios in which AI trading can be involved in market accidents, misconduct, or criminal activities. These four scenarios include: (i) 'AI as a victim', (ii) 'traditional unintended consequences', (iii) 'conscious misuse by humans', and (iv) 'autonomous misconduct by AI' (Chapter 3.2). Then, shifting our analytical focus to artificial trading agents based on DRL, we will examine both technical and practical challenges that may ultimately disinhibit AI trading potential to engage in market manipulation in an autonomous way (Chapter 3.3). Subsequently, we will discuss, from a conceptual viewpoint, the likelihood of the risk of market manipulation by autonomous AI trading though a series of case studies, using the proprietary trading industry as an illustrative domain (Chapter 3.4). Eventually, the chapter concludes with a summary of key findings (Chapter 3.5).

3.1 Market Integrity and the Fight Against Market Manipulation

As an ideal, the institutional role of capital markets is to enable the efficient allocation of financial resources and facilitate appropriate risk sharing among market participants.[298] To support this goal, financial regulation plays a vital role in promoting, responsible market conduct by fostering the principles of transparency, fairness, and accountability within financial markets. Among its many objectives, for instance, financial regulation aims to provide investors with fair access to accurate information, recognising that inaccurate market prices impair the efficient allocation of resources.[299] The pursuing of this objective helps instil confidence in financial markets and protect consumers from fraudulent and abusive practices.[300] To this end, regulatory authorities establish and enforce rules and standards governing market participants' behaviour of

[298] *E.g.*, Luc Laeven, 'The Development of Local Capital Markets: Rationale and Challenges' (2014) IMF Working Paper 1 <https://www.imf.org/external/pubs/ft/wp/2014/wp14234.pdf> accessed 17 July 2024; *see also* Avgouleas (n 297) 158; Yadav (n 66) 1631-1632; Fox, Glosten, and Rauterberg (n 70) 72.

[299] *Cf*. Avgouleas (n 297) 167-170; John Armour and others, *Principles of Financial Regulation* (Oxford University Press 2016) 184.

[300] John Armour and others (n 299) 182-183.

market, monitor market activity, and investigate and prosecute violations of these rules.[301]

Certain market behaviours are inherently deemed improper due to their detrimental impact on markets.[302] As such, financial regulation generally prohibits these conducts as forms of market abuse. This concept encompasses various illegitimate practices undermining the free and fair nature of capital markets. As one of the most harmful and insidious forms of market abuse, market manipulation has always been the focus of financial regulators.[303] In short, market manipulation involves deliberate attempts by malicious actors to disrupt the normative functioning of capital markets, thereby interfering with their free and fair operation in order to gain private benefits.[304] This pathologic economic phenomenon involves actions aimed at artificially altering the prices of financial instruments or influencing market activity through deceptive means, with the ultimate goal of inducing other investors to trade in the hoped-for direction.[305]

Given that market mechanisms alone may be insufficient in countering market abuse, financial regulation seeks to promote positive market behaviours by prohibiting harmful practices and discouraging their perpetration through the threat of sanctions.[306] Due the undisputable socially harmful effects of market manipulation,[307] legal prohibitions against this form of market abuse exist in most legal systems.

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301 Ibid 190-194.

302 Avgouleas (n 297) 148.

303 *See, e.g.*, Fox, Glosten, and Rauterberg (n 70) 67.

304 *See, e.g.*, footnote n. 20.

305 Avgouleas (n 297) 107.

306 *See* Chapter 5.2; *but see* discussion in Chapter 3.2.D.

307 *E.g.*, Avgouleas (n 297) 212-213; *see also* Fox, Glosten, and Rauterberg (n 70), addressing the harmful welfare effect of open market manipulation, and how financial law and regulation should deal with these forms of market abuse.

However, not only the legal definition of market manipulation,[308] but also the scope of application of the corresponding prohibition varies widely among jurisdictions.[309]

The use of technology to facilitate illicit market practices is certainly not a new phenomenon. With the advancement of trading technology, malicious actors face today great incentives to research and deploy powerful tools to optimise against the system, benefitting from the implementation of manipulative strategies.[310] Scientific research provides empirical evidence about the use of trading technology in market manipulation.[311] Additionally, the growing number of prosecuted cases have highlighted the liability of market participants who engage in market manipulation through algorithmic trading strategies, particularly in the context of HFT.[312]

308 In the US, the prohibition against market manipulation is addressed through various statutes and legal provisions. Mainly, Section 9(a)(2) of the Securities and Exchange Act prohibits transactions in securities that create active trading or manipulate prices with the purpose of inducing others to buy or sell those securities. However, the jurisprudence surrounding this provision has not provided yet a clear legal framework for determining what exactly constitutes an 'illegitimate purpose' in trading activity. *See, e.g.*, discussion in Fox, Glosten, and Rauterberg (n 70) 114-117, who, by looking at the US case law, argue that this rule has only had a minimal role in developing the manipulation jurisprudence. On the other hand, the prohibitions under Section 10(b), particularly Rule 10b-5, have a broader scope in combating market manipulation by prohibiting manipulative conduct that operates as fraud or deceit upon other market participants. *See* 15 U.S.C. § 78j(b) and 17 C.F.R. § 240.10b-5. There is a long-standing debate among legal scholars and courts regarding whether trading activity alone can constitute market manipulation or if an additional element is required for prosecution. *See, e.g.*, Fox, Glosten, and Rauterberg (n 70) 118-122. Additionally, the Commodity and Exchange Act includes specific provisions prohibiting market manipulation of commodity prices, such as the prohibition of 'spoofing'—i.e. intentionally submitting trading orders with the intention to cancel them before execution to deceive other market participants—under the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act. However, the challenge of dealing with intent-based tests for algorithmic market manipulation is a subject of discussion among legal scholars. *See, e.g.*, Scopino (n 71) 293.

309 In the US, for instance, Section 9(a)(2) does not apply to OTC financial instruments. Additionally, the EU market abuse regulations does not cover spot foreign exchange (FX) contracts. *See* ESMA, 'MAR Review Report' (23 September 2020) ESMA70-156-2391, 26.

310 *See, e.g.*, Jón Danielsson, *The Illusion of Control* (Yale University Press 2022) 217.

311 *See, e.g.*, Jiading Gai, Chen Yao, and Mao Ye, 'The Externalities of High-Frequency Trading' (2013) WBS Finance Group Research Paper No. 180, 6-7 <https://ssrn.com/abstract=2066839> accessed 17 July 2024, who provide interesting empirical evidence about some HFT manipulative strategies on US-traded stocks.

312 Despite the inherent difficulties faced by enforcement bodies in detecting and prosecuting sophisticated forms of market manipulation enabled by trading technology—such as spoofing—, there has been a notable increase in successfully prosecuted cases in recent years. For instance, the US witnessed a landmark case in 2015 when trader Michael Coscia was found guilty and sentenced to a

Nevertheless, it is undeniable that financial regulators are facing mounting challenges in keeping pace with the constantly evolving landscape of algorithmic trading, especially in fighting sophisticated forms of market manipulation, which can span across multiple assets, markets, and international borders.[313] As a consequence, there is a pressing need to establish more robust monitoring and enforcement mechanism to fight market abuse due to growing risks introduced by technology innovation in financial trading. Against this backdrop, in the following section, we conceptually explore the four basic scenarios in which trading algorithms may result in market misconduct.

3.2 Algorithmic Market Manipulation: The Four Basic Scenarios

The unconscious, negligent, or malicious use of AI in financial trading can cause a number of market inefficiencies, potentially resulting in systemic instability and

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three-year jail term for spoofing in the US futures market. This constitutes the very first prosecuted case against spoofing in the history of finance. *See* United States v. Coscia, Case No. 14 CR 551 (N.D. Ill. Apr. 16, 2015). Another significant example involves trader Navinder Singh Sarao, who faced criminal prosecution and was convicted of spoofing US future markets. *See* United States v. Navinder Singh Sarao, Case No. 15 CR 75 (N.D. Ill. 9 November 2016). More recently, prominent cases have involved *JP Morgan Chase & Co*, one of the leading global investment firms, which was prosecuted and found guilty of manipulating the price of US Treasury securities through trading strategies designed to deceive other market participants. *See* J.P. Morgan Sec. LLC, File No. 3-20094 (2020) (admin. order). Additionally, the UK regulators had imposed fines on three bond traders employed at *Mizuho Financial Group* for abusive trading practices involving the Italian government bond futures. *See* FCA, 'FCA Publishes Decision Notices against Three Bonds Traders for Market Manipulation' (7 December 2022) Press Release <https://www.fca.org.uk/news/press-releases/fca-publishes-decision-notices-against-three-bond-traders-market-manipulation> accessed 17 July 2024. These examples demonstrate the growing commitment of financial regulators to combating innovative and sophisticated forms of market manipulation enabled by trading technology. For a summary of recent enforcement efforts in the US and UK, see James Cavoli and others, 'US & UK Litigation Briefing: Spoofing under US and UK Law' (*Milbank*, 2021) <https://www.milbank.com/a/web/155025/Litigation-Client-Alert-Spoofing-under-US-and-UK-law.pdf> accessed 17 July 2024.

313 *See, e.g.*, IOSCO (n 20) 23-29. The report highlights the need for supervisory cooperation among all market stakeholders to deal effectively with forms of cross-market and cross-border manipulations). *See also* Austin (n 79), who discusses recent developments in global capital markets' structure associated with the advent of algorithmic trading and their implication for financial regulators and supervisors to safeguard market integrity.

rendering global capital markets more fragile.[314] From a conceptual point of view, we can identify at least four basic scenarios when examining the potential of AI trading to cause market disruption, distortion, and harm. As discussed in more detail below, these scenarios encompass instances of: (A) operational vulnerability (i.e. 'AI as a victim'), (B) 'traditional unintended consequences', (C) 'conscious misuse by humans', and (D) even cases of 'autonomous misconduct by AI trading'.

As we delve deeper into each scenario, we will uncover incremental implications for the effectiveness of regulatory requirements and market conduct rules. In particular, concerning the risks of market manipulation, regulatory concerns mainly revolve around the varying degree of autonomy exhibited by AI trading systems in relation to their human users. As autonomy levels increase, questions about the effective governance of AI trading systems and the regulation of their market conduct intensify.

A. AI as a victim

The first basic scenario involves cases in which a given AI trading system becomes a victim of a market accident or crime.[315] Under such circumstances, AI systems are subject to external actions that negatively impact their operational performance and integrity. For instance, an AI system could be deceived or even hacked, resulting in it being manipulated by a third party driven by some personal interests. To illustrate, consider the scenario of a cybersecurity breach in which a malicious agent (e.g., a

314 *See generally* Jón Daníelsson, Robert Macrae, and Andreas Uthemann, 'Artificial Intelligence and Systemic Risk' (2022) 140 Journal of Banking and Finance, Article 106290 <https://doi.org/10.1016/j.jbankfin.2021.106290> accessed 17 July 2024.

315 *See generally* Lorenzo Pupillo and others, 'Artificial Intelligence and Cybersecurity: Technology, Governance and Policy Challenges' (2021) CEPS Task Force Report, Brussels, 57-59 <https://www.ceps.eu/wp-content/uploads/2021/05/CEPS-TFR-Artificial-Intelligence-and-Cybersecurity.pdf> accessed 17 July 2024.

terrorist group or other criminal organisation) seeks to sabotage the normal functioning of a particular AI trading system.[316]

Alternatively, consider a situation where a human trader attempts to mislead a rival trading algorithm, inducing it to make errors.[317] While these examples may seem unrealistic, it is essential to acknowledge that potential attackers could attempt to exert influence over the behaviour of a targeted algorithmic trading system. They might do this by either disabling specific system's functionalities or exploiting its technical vulnerabilities, such as manipulating input data streams. For instance, an attacker could corrupt the training dataset, causing the AI system to make inaccurate predictions or engage in undesired actions.[318] This is especially true for ML algorithms, which, being highly data-dependent, have a high susceptibility to input manipulation, making them vulnerable to adversary attacks.[319]

All in all, this first scenario underscores the critical need for robust security measures and continuous monitoring of AI trading systems to safeguard them from potential external threats.

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[316] Ibid 59-62.

[317] *See* Jakob Arnoldi, 'Computer Algorithms, Market Manipulation and the Institutionalization of High Frequency Trading' (2015) 33(1) Theory, Culture & Society 29 <https://doi.org/10.1177/0263276414566642> accessed 17 July 2024.

[318] Pupillo and others (n 315) 59-62.

[319] *See* Elior Nehemya and others, 'Taking Over the Stock Market: Adversarial Perturbations Against Algorithmic Traders' in Yuxiao Dong and others (eds), *Machine Learning and Knowledge Discovery in Databases. Applied Data Science Track. ECML PKDD 2021. Lecture Notes in Computer Science Vol 12978* (Springer Cham 2021) 221-236 <https://doi.org/10.1007/978-3-030-86514-6_14> accessed 17 July 2024; Fengsuo Bai and others, 'PALM: Preference-based Adversarial Manipulation against Deep Reinforcement Learning' (*The Eleventh International Conference on Learning Representation (ICLR 2023)*, 2023) <https://openreview.net/pdf?id=YzOEjv-7nP> accessed 17 July 2024, demonstrating the vulnerability of DRL agents to adversarial attacks through a preference-based adversarial manipulation approach that is capable of targeting and impair the functioning of such agents.

B. Traditional unintended consequences

The second scenario entails instances in which AI trading gives rise to unintended consequences, resulting in market accidents such as flash crashes. These occurrences are typically due to some operational failure (e.g., a bug in the system) attributable to poor human design, use, or control.[320] For instance, some of the most significant cases of exceptional market disruption caused by trading algorithms may actually be due to faulty design leading to software failures. One such case is the spectacular operational failure suffered by *Knight Capital* in 2012, which caused a market crash on the *New York Stock Exchange*.[321] The investment firm, which faced bankruptcy as a result of its losses from the incident, had employed an automated routing system for trade execution that spiralled out of control. The effects of this incident put considerable pressure on the markets, causing severe disorders in the prices of numerous stocks. However, by the time the defective trading software was fixed, losses had already soared to approximately forty-six million US dollars, bringing the investment firm perilously close to insolvency until it was acquired by a competitor.[322]

In addition to accidents resulting from human negligence, there are also cases where algorithmic trading systems may cause market disruptions, despite the fact that their developers and users have exercised due care. For instance, technical flaws in trading platforms can lead to abnormal trading conditions that unfairly disadvantage certain market participants.[323] Even with deterministic AI systems, the unintended

[320] *See, e.g.*, Kirilenko and Lo (n 49) 60-67.

[321] *See* Knight Capital Americas LLC, File No. 3-15570 (Securities and Exchange Commission, 16 October 2013) <https://www.sec.gov/litigation/admin/2013/34-70694.pdf> accessed 17 July 2024.

[322] *See, e.g.*, discussion in Yadav (n 65) 1047.

[323] Market accidents caused by algorithms can also result from operational failures of trading platforms. *Cf.* Quoine Pte Ltd v B2C2 Ltd [2020] SGCA(I) 02. For a discussion on this case, see Kelvin FK Low and Eliza Mik, 'Lost in Transmission: Unilateral Mistakes in Automated Contracts' (2020) 136 Law Quarterly Review 563 <https://search.informit.org/doi/10.3316/agispt.20201027038767> accessed 17 July 2024.

consequences of algorithmic trading can often defy human understanding, thereby complicating effective human control as well as law enforcement efforts. Under this second scenario, despite the general challenges in dealing with the unintended consequences of automated trading, financial regulators still possess access to the necessary legal concepts and tools to eventually address issues of human accountability and liability.[324]

Nevertheless, the potential for trading algorithms to cause unintended consequences underscores the need for their users to have robust risk management practices and conduct ongoing surveillance in order to mitigate the risks of accidents leading to market disruptions.

C. Conscious misuse by humans

The third scenario involves more dishonest circumstances, where rogue algorithms are intentionally created and used by humans for illicit purposes. In these cases, algorithmic market abuse is premeditated and, thus, 'by design'. Malicious actors purposefully design, develop, and use trading systems to perpetrate unfair market practices, with the goal of illicitly profit from opportunities that would not otherwise be available to them.[325] The potential for AI trading to circumvent market conduct rules can be either embedded within the code itself or acquired through subsequent training.[326] In this last regard, human experts can impart knowledge to their AI systems, based on empirical data (e.g., via back-testing) or simulated market

[324] *Cf.* Yadav (n 65) 1079, who argues that interactions and correlation between trading algorithms frustrate enforcement actions.

[325] *See, e.g.*, Scopino (n 71); Lin (n 70); Yadav (n 78); Fletcher (n 75).

[326] *See, e.g.*, Bathaee (n 76) 909-912.

environments, teaching them how to 'discover' manipulation while pursuing profit-maximising business objectives.[327]

A notable example of humans creating trading algorithms to manipulate markets is the first case of HFT manipulation prosecuted by US authorities in 2014. During the period between June and December 2009, *Athena Capital*, an HFT firm active in the US equity markets, utilised its bandit algorithm, *Gravy*, to manipulate the closing prices of numerous publicly traded securities on *NASDAQ*, the second-largest US exchange, by exploiting order imbalances in electronic order books. Through this scheme, the investment firm was able to establish a dominant position in those stocks, even if only for the final seconds of the trading day, enough to enable the making of extra profits.[328]

Cases that fall under this third scenario are known for the difficulties they create for the enforcement of market conduct rules. In fact, holding individuals accountable for the misconduct of their trading algorithms can be a quite demanding task for regulatory authorities. Effective enforcement requires substantial resources at disposal for regulators to detect and prosecute instances of manipulation. In reality, however, enforcement outcomes are often limited by the lack of adequate tools and expertise enforcement bodies suffer compared to private financial sector organisations, as they tend to lag behind.[329] This can be highly problematic as ascertaining liability for AI-

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327 *But see* Takanobu Mizuta, 'Can an AI Perform Market Manipulation at Its Own Discretion?—A Genetic Algorithm Learns in an Artificial Market Simulation' (2020) 2020 IEEE Symposium Series On Computational Intelligence 407, 407-408 and 410-411 <https://doi.org/10.1109/SSCI47803.2020.9308349> accessed 17 July 2024, arguing that traditional learning methods that rely solely on back-testing are unable to 'teach' AI trading how to effectively manipulate market prices as they do not adequately address liquidity constraints.

328 According to the SEC decision, Athena Capital was guilty of violating Rule 10b-5 of the Securities Exchange Act of 1934 and agreed to pay a 1 million US dollars administrative fine. *See* In the Matter of Athena Capital Research, LLC No. 3-16199 (*SEC*, 16 October 2014).

329 *See, e.g.*, Andrew W Lo, *Adaptive Markets: Financial Evolution at the Speed of Thought* (Princeton University Press 2019) 358-360, who notes that it took US enforcement authorities more than six years to criminally prosecute Mr Navinder Sarao for committing 'spoofing' and held responsible for contributing to the Flash Crash of May 2010.

enabled misconduct and resulting harm is a complex undertaking. First, it is not always easy to discern sophisticated forms of manipulation in vast volumes of genuine trading activity. Additionally, in most jurisdictions, prosecutors and plaintiffs alike must provide compelling evidence of the intent or other relevant mental state ('scienter') of the individuals employing manipulative strategies.[330] This assessment is often arduous because it requires regulators to determine the concrete participation in liability of every agent possibly involved in the manipulation practice. Such a determination is nevertheless necessary to allocate the exact extent of liability among a vast and often opaque array of potential individuals associated with a given AI project.[331]

Beyond these general considerations, we should point out that the increasingly widespread adoption of AI trading techniques, which are increasingly sophisticated and sometimes opaque, may leave capital markets increasingly susceptible to market abuse. Mainly, these risks are due to the growing information asymmetry and knowledge disparity between financial firms and regulators regarding the use of AI trading and its potential to result in market misconduct.[332]

D. Autonomous misconduct by AI

The fourth scenario represents an extreme and hitherto unprecedented case, only made possible by continued progress in ML. Specifically, thanks to ML, trading agents become so capable that, in the course of their autonomous trading activity, they are

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330 On the legal problem of proving human intent behind algorithmic trading and manipulation, see Yadav (n 65) 1073-1076; Scopino (n 71) 255-257.

331 *See, e.g.*, Yadav (n 65); Flecther (n 75); *see also* Jonathan ME Tan, 'Non-Deterministic Artificial Intelligence Systems and the Future of the Law on Unilateral Mistakes in Singapore' (2022) 34(1) Singapore Academy of Law Journal 91 <https://journalsonline.academypublishing.org.sg/Journals/Singapore-Academy-of-Law-Journal/Current-Issue/ctl/eFirstSALPDFJournalView/mid/494/ArticleId/1732/Citation/JournalsOnlinePDF> accessed 17 July 2024, who discusses the issue from a common law perspective using Singapore's legal framework as a case study.

332 *See, e.g.*, footnote n. 310.

able to discover ways to manipulate markets as an optimal and rational strategy to achieve the best results. Importantly, in this fourth scenario, manipulation occurs regardless of the specific human intent behind AI trading.[333] This new and unprecedented scenario is the most challenging for both investment firms, obliged to meet regulatory requirements and comply with market conduct rules, and financial regulators, who instead are tasked with safeguarding market integrity.

Unlike deterministic AI systems, ML trading agents might become capable, through self-learning, of uncovering trading strategies beyond the original intentions and predictable outcomes by human experts. The latter, in turn, may not be able to explain the market conduct of their trading systems. This equates to the black box problem, where the inner workings and validity of the AI-generated outcomes are hard to comprehend. While human creators and users are expected to be aware of the capabilities and limitations of their AI tools—including the various components and data quality (such as, e.g., statistical representativeness and bias)—they may nevertheless struggle to fully comprehend and reason about *why* and *how* their algorithms arrived at specific trading decisions.[334] This is particularly the case for those trading systems employing DL methods,[335] including DRL agents as discussed in Chapter 2.[336] Although such methods enable powerful optimisations, their results and behaviours can be opaque, leading to concerns about transparency and thus

333 *See generally* Thomas C King and others, 'Artificial Intelligence Crime: An Interdisciplinary Analysis of Foreseeable Threats and Solutions' (2020) 26 Science and Engineering Ethics 89 <https://doi.org/10.1007/s11948-018-00081-0> accessed 17 July 2024; *see also* Bathaee (n 76), who conceptualises some possible scenarios of manipulation by autonomous AI conduct.

334 The black box problem, thus, reveals the risks involved in entrusting tasks to AI systems even in cases where it is possible to predictive how it will work.

335 *E.g.*, Bathaee (n 76) 901-903.

336 *See* Chapter 2.4 and 2.5.B.

accountability.[337] All this can greatly hinder the deployment of trustworthy applications.

This fourth scenario of market misconduct by autonomous AI trading raise fundamental questions relating to ensuring effective regulatory compliance by investment firms as well as enforcement of market conduct rules by competent authorities. From a compliance standpoint, the inability of users to meaningfully control the market behaviour of their trading algorithms is problematic. Users should always be in a position to do so in order to fulfil their regulatory obligations, and a lack of control amounts to un-ethical implementation and use of trading technology.[338] Issues of control, thus of compliance, are necessarily linked to the black box problem, which entail both technical and legal considerations often framed in terms of AI explainability.[339]

From an enforcement perspective, in turn, the ability to explain algorithmic decision-making and resulting outcomes becomes crucial when addressing cases of AI misconduct and harm, as law enforcement authorities need to ascertain liability by considering the specific contributions of different individuals within an investment firm in order to ensure effective enforcement and deterrence. Undoubtedly, the autonomous and black box nature of certain AI systems adds an additional layer of complexity when applying liability rules safely and correctly.[340] In sum, this fourth

337 *Cf.* Zachary C Lipton, 'The Mythos of Model Interpretability: In Machine Learning, the Concept of Intrepretability is both Important and Slippery' (2018) 16(3) Queue 31 <https://doi.org/10.1145/3236386.3241340> accessed 17 July 2024, arguing that the trade-off between model accuracy and explainability in ML methods can be interpreted very differently depending on different stakeholders and their purposes.

338 *See, e.g.*, Lenglet (n 60) 51 and 57-58; Bacoyannis and others (n 199) 6; *see also* Michele Mozzarelli, 'Digital Compliance: The Case for Algorithmic Transparency' in Stefano Manacorda and Francesco Centonze (eds), *Corporate Compliance on a Global Scale* (Springer Cham 2021) 259-284 <https://doi.org/10.1007/978-3-030-81655-1_12> accessed 17 July 2024.

339 *See* footnotes n. 34, 36-39 and 54 and accompanying text.

340 *See* discussion in Chapter 6.1 and 6.3.

scenario poses novel and unprecedent risks to the safe application of financial regulation, potentially resulting in threats to market integrity. It raises critical questions about the ability of investment firms to control their trading systems and exacerbates the challenges faced by public authorities in regulating market behaviour and enforcing market conduct rules in the context of ML-powered algorithmic trading.

Using RL research as an illustrative case, in the remaining of this chapter, we will discuss how autonomous AI trading agents may pave the way for new forms of algorithmic market abuse. These include the optimisation of both old and novel market manipulation techniques, as well as unprecedented risks of algorithmic collusion. However, we will also discuss both practical and technical challenges that may ultimately impede RL-based agents from autonomously discovering manipulation as an optimal and rational strategy for maximising rewards.

3.3 Autonomous AI Trading Agents and Market Manipulation

ML methods provide investment firms with the opportunity to research and deploy innovative tools that can enhance the profitability of trading operations by solving optimisation problems. However, as will be examined in this section more closely, we need to address the dark side associated with the application of such advanced technology: AI trading may inadvertently result in optimised forms of market manipulation to the detriment of other market participants. As a result of advancements in ML, new and insidious forms of market misconduct may emerge that are characterised by autonomous trading conduct by AI trading agents.

Due to increased analytical capabilities, swift action, and widespread presence in the market, AI trading could alter the traditional mechanics of market manipulation as an economic phenomenon. Specifically, AI trading has the potential to alter the space-time dimensions at which market events take place,[341] such as flash crashes,

[341] *Cf.* Thomas Skou Grindsted, 'Algorithmic Finance: Algorithmic Trading across Speculative Time-Spaces (2022) 112(5) Annals of the American Association of Geographers 1390 <https://doi.org/10.1080/24694452.2021.1963658> accessed 17 July 2024, contending that

market manipulation, and their contagion effects. As known, the fast-paced and interconnected nature of algorithmic trading strategies has introduced the occurrence of ultra-fast extreme events, including instances of 'micro-manipulation'.[342] In this context, the optimisation capabilities of ML methods may make it easier for market actors to implement, more or less consciously, profitable manipulative strategies. In this sense, trading only-based forms of manipulation—notoriously deemed difficult to perform without incurring substantial risks of loss and/or detection—might become easier to accomplish. Moreover, optimised market manipulation enabled by AI trading may present significant challenges for financial regulators and supervisors to ensure effective market surveillance and punishment of misconduct. This, in turn, leaves markets vulnerable to rampant abuse, thus exposing aggrieved parties to unprotected economic interests.

Nevertheless, it should be acknowledged that the actual potential of an autonomous AI trading agent to successfully manipulate markets is contingent upon a number of factors. The latter encompass technical considerations related to specific ML methods employed and broader micro- and macro-economic aspects (such as market access, market power, market structure, and exposure to financial risks).[343] Before conceptually analysing these risks through some case studies, it may be

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algorithmic trading introduces speculative space-times, creating diverse temporalities among market participants and engaging in speculation across geographical locations and distances. HFT-based strategies, in particular, alter market logics and dynamics, leading to the privatisation of public market information in sub-second fractions of time.

342 *Cf.* Neil Johnson and others (n 117).

343 *Cf.* Edward Leung and others, 'The Promises and Pitfalls of Machine Learning for Predicting Stock Returns' (2021) 3(2) The Journal of Financial Data Science 21 <https://doi.org/10.3905/jfds.2021.1.062> accessed 17 July 2024. In comparing ML methods to more traditional approaches, the authors assert that the success of any ML-based trading strategy necessarily depends on its ability to manage risk effectively and execute trades efficiently. Hence, the ability of an ML-powered trading system to face and adapt evolving market conditions while optimising risk exposure is crucial for achieving favourable outcomes, even in the context of market manipulation.

appropriate to elaborate on the determinants of market manipulation by autonomous AI.

A. Can AI learn to manipulate markets autonomously?

The question of whether AI trading agents can, through self-learning, autonomously discover ways to manipulate markets as an optimal strategy in pursuit of their pre-defined trading goals is not only gaining attention from the scientific community,[344] but also beginning to cause concerns among more vigilant financial regulators.[345]

344 Indeed, the scientific community is witnessing a rising interest in exploring the risks associated with market manipulation facilitated by ML algorithms. *See, e.g.*, Enrique Martínez-Miranda and others, 'Learning Unfair Trading: A Market Manipulation Analysis from the Reinforcement Learning Perspective' in *Proceedings of the 2016 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS)* (IEEE 2016) 103-109 <https://doi.org/10.1109/EAIS.2016.7502499> accessed 17 July 2024, discussing the causes that can lead a RL trading agent to discover and enter manipulative strategies, such as 'spoofing' and 'pinging'; Michael P Wellman and Uday Rajan, 'Ethical Issues for Autonomous Trading Agents' (2017) 27(4) Minds and Machines 609 <https://doi.org/10.1007/s11023-017-9419-4> accessed 17 July 2024, who conceptualise the risks of order-based forms of manipulation made possible by advanced algorithms; Mizuta (n 327) 407-412, who develops a DL-based agent, using genetic algorithms, able to discover market manipulation as an optimal strategy in artificial market simulations; Megan Shearer, Gabriel Rauterberg, and Michael P Wellman, 'Learning to Manipulate a Financial Benchmark' in *ICAIF '23: Proceedings of the Fourth ACM International Conference on AI in Finance* (ACM 2023) 592-600 <https://doi.org/10.1145/3604237.3626847> accessed 17 July 2024, finding evidence via in-lab simulations of RL agents' potential to engage in financial benchmark manipulation; David Byrd, 'Learning Not to Spoof' in Daniele Magazzeni and others (eds), *ICAIF '22: Proceedings of the Third ACM International Conference on AI in Finance* (ACM 2022) 139-147 <https://doi.org/10.1145/3533271.3561767> accessed 17 July 2024, demonstrating the tendency of RL-based trading agents to discover manipulative strategies such as 'spoofing' as an optimal strategy in the course of their autonomous activity; Michael S Barr and others, 'The Coming Failure of Manipulation Law? An Experimental Approach with Deep Reinforcement Learning' (2023) Working Paper <https://law-economic-studies.law.columbia.edu/sites/default/files/content/Barr%20et%20al_Reinforcement%20Learning,%20Algorithms,%20&%20Manipulation%20Law_rev%202021%2010%2019_7%20pm.pdf> accessed 17 July 2024, providing in-lab evidence of the potential of DRL trading agents to engage in benchmark manipulation leveraging deceptive strategies such as 'spoofing'.

345 In the author's opinion, the Dutch financial regulator stands out as one of the public authorities most actively engaged in researching risks of market manipulation introduced by specific trading practices based on ML methods, particularly RL. *See generally* AFM (n 105). In fact, the AFM has initiated a research collaboration with The Alan Turing Institute to better understand the techno-economic characteristics of manipulative strategies, also those involving the use of ML. *See* Álvaro Cartea and others, 'Statistical Predictions of Trading Strategies in Electronic Markets' (2023) SSRN preprint 1 <https://ssrn.com/abstract=4442770> accessed 17 July 2024. Although less proactively, other financial regulators around the world have also begun to monitor these risks more closely. *See, e.g.*, BoE and FCA, 'DP5/22 – Artificial Intelligence and Machine Learning' (2022) Discussion Paper 5/22, para 3.22 <https://www.bankofengland.co.uk/prudential-

One possible way to assess the risk of market manipulation by autonomous AI trading agents would be to focus our analysis on the specific ML class of RL algorithms. As discussed in Chapter 2, RL-based trading agents are able to learn optimal course of action through trial and error in order to maximise cumulative rewards by receiving feedback from their operative environment. We should, however, make it clear that existing evidence of market participants' employment of RL methods to deploy artificial trading agents is rare, if not non-existent. On one hand, known cases of prosecution for algorithmic market manipulation do not shed much light on the specific ML methods employed by malicious market actors. On the other hand, intangible assets such as trading systems and strategies are generally protected under intellectual property (IP) rights, not allowing researchers in the field to gain valuable insights into the precise level of technological sophistication that investment firms achieve.

This lack of information should nevertheless not constitute a valid excuse to inhibit our research efforts to shed light on the intricate relationship between RL and market manipulation. Indeed, there is at least some initial evidence from in-lab studies that RL-based trading agents, while pursuing the goal of profit maximisation, may develop autonomously the ability to discover manipulation as an optimal and rational strategy to achieve the best rewards. Importantly, state-of-the-art research suggests that RL trading agents may engage in forms of market manipulation even without being expressively designed or instructed to do so.[346] Basically, the tendency of RL agents to discover manipulation depends on specific learning frameworks. Algorithmic trading agents may develop an aptitude for manipulation either through offline (e.g., via back-

regulation/publication/2022/october/artificial-intelligence> accessed 17 July 2024 [hereinafter BoE and FCA IV]; Consulich and others (n 106); BoE and FCA, 'FS2/23 – Artificial Intelligence and Machine Learning' (October 2023) Feedback Statement 2/23 <https://www.bankofengland.co.uk/prudential-regulation/publication/2023/october/artificial-intelligence-and-machine-learning> accessed 17 July 2024 [hereinafter BoE and FCA V].

346 *E.g.*, Martínez-Miranda and others (n 344); Shearer, Rauterberg, and Wellman (n 344); Byrd (n 344).

testing or in simulated market environments)[347] or online learning (i.e. while operating live in markets).[348] However, in light of these findings, the scenario of market manipulation by autonomous AI seems at least conceptually feasible. However, since existing supporting evidence is based solely on experimental studies, it still needs to be determined to which extent these risks may arise in real-life market settings.

The potential of RL trading agents to engage in manipulative conduct is one good example of the so-called problem of 'value alignment'[349] in the context of AI, particularly ML applications.[350] This term generally refers to the challenge of ensuring that AI systems and their behaviour are aligned with human values and user preferences. As well-exemplified by the case of RL trading agents resulting in unwanted manipulation, this problem arises when AI systems, especially those enjoying high levels of autonomy, make decisions and take actions leading to undesirable outcomes.[351] Therefore, unconstrained RL agents may lead to a situation in which they inadvertently learn to manipulate markets, regardless of the real motives by human practitioners motivating their deployments in markets.[352]

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347 Ibid; *but see* footnote n. 327.

348 *Cf.* Hal Ashton, 'Definitions of Intent Suitable for Algorithms' (2022) 31 Artificial Intelligence and Law 515, 519-520 <https://doi.org/10.1007/s10506-022-09322-x> accessed 17 July 2024; *but see* Sun, Wang, and An (n 196) 20-21, who state that "*learning through directly interacting with the real market is risky and impractical*".

349 The 'value alignment' problem in AI and ML research generally refers to the fact that a given AI system's objective function may not always be aligned with the values and goals of its various human stakeholders. *See, e.g.*, Jessica Taylor and others, 'Alignment for Advanced Machine Learning Systems' in S Matthew Liao (ed), *Ethics of Artificial Intelligence* (Oxford University Press 2020) 342-382 <https://doi.org/10.1093/oso/9780190905033.003.0013> accessed 17 July 2024, examining the concept of AI alignment in the context of RL agents.

350 *E.g.*, Byrd (n 344) 140.

351 *See generally* Soares and Fallenstein (n 43) 103-105; *see also* Iason Gabriel, 'Artificial Intelligence, Values, and Alignment' (2020) 30 Minds and Machines 411 <https://doi.org/10.1007/s11023-020-09539-2> accessed 17 July 2024, discussing the problem of value alignment from a philosophical perspective. The author clarifies the various meanings, both positive and negative, that the term AI alignment can take on according to the point of view of various stakeholders.

352 *E.g.*, Byrd (n 344) 140-141.

In RL, the 'reward function' plays a vital role in constraining agents' actions and align them to users' goals, preferences, and values.[353] Poorly-specified reward functions may induce an RL agent to subvert its environment by giving exclusive priority to the acquisition of rewards signals disregarding any consideration to other measures/variables of success.[354] To use the domain of videogames again as an illustrative example, mis-specified reward functions can cause RL agents to engage in some sort of cheating behaviour, discovering and exploiting bugs in their environments, such as glitches that enables them to win more easily.[355] Although in game environments the risks posed by RL agents are somewhat limited, in the real world unwanted actions can have highly negative consequences to the point of causing irreparable effects and even damage.[356] However, in large, complex, and highly interconnected systems—such as in algorithmic trading—, these risks can often pass undetected. In such complex application domains, it may be extremely tough to timely evaluate when a given system is not working as intended or is even altering user preferences to make its tasks easier.[357] These risks underpin the need for human experts to take all the engineering efforts to ensure safe development and use of RL methods.

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[353] *See* Chapter 2.3.C.

[354] *See, e.g.*, Dario Amodei and others, 'Concrete Problems in AI Safety' (2016) arXiv preprint 1, 7-11 <https://arxiv.org/pdf/1606.06565.pdf> accessed 17 July 2024; Hal Ashton, 'Causal Campbell-Goodhart's law and Reinforcement Learning' (2021) arXiv preprint 1, 6 <https://arxiv.org/pdf/2011.01010.pdf> accessed 17 July 2024.

[355] Ibid 9; OpenAI (n 192), reporting the occurrence of this behaviour in CoastRunners, a video game that requires players to run a boat race and earn points by hitting targets along the way to win. Specifically, the RL-based agent found that to be victorious it did not necessarily have to finish the race but rather chase after the greatest number of targets.

[356] Ibid.

[357] *E.g.*, Hal Ashton and Matija Franklin, 'The Problem of Behaviour and Preference Manipulation in AI Systems' in Gabriel Pedroza and others (eds), *SafeAI 2022 – Artificial Intelligence Safety 2022: Proceedings of the Workshop on Artificial Intelligence Safety 2022 (SafeAI 2022) co-located with the Thirty-Sixth AAAI Conference on Artificial Intelligence (AAAI2022)* (CEUR-WS.org 2022) <https://ceur-ws.org/Vol-3087/paper_28.pdf> accessed 17 July 2024.

In principle, there are two main methods for human experts to constrain their RL agents in order to ensure safe and reliable applications. One first option entails the implementation of hard-coded limitations in the RL reward function.[358] The validity of this method, however, seems constrained by the impossibility of foreseeing all necessary limits to be encoded in the system, especially when dealing with complex systems and/or complex environments.[359] As an alternative or complementary option, which do not require direct access to the reward function, human experts can communicate their preferences to enable RL agents to better 'understand' their goals by providing feedback during the learning process.[360] Indeed, only in the last few years 'Reinforcement Learning with Human Feedback' (RLHF) has emerged as a frontier branch of research within the ML scientific community. In part, the interest around RLHF methods is partly motivated by the potential negative consequences for society associated with blandly trusting powerful AI applications (e.g., Generative AI models such as ChatGPT) in high-risk domains for human life and fundamental rights.[361] While recognising the innovative nature of Generative AI applications in financial trading,[362]

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358 *E.g.*, Byrd (n 344), who also proposes a possible solution to make sure RL agents avoid engaging in manipulative practices such as spoofing.

359 Amodei and others (n 354) 14.

360 *See, e.g.*, Paul F Christiano and others, 'Deep Reinforcement Learning from Human Preferences' (2023) arXiv preprint 1 <https://doi.org/10.48550/arXiv.1706.03741> accessed 17 July 2024, discussing a method on how to implement non-expert human preferences on (D)RL agents in a variety of application domains, including video games.

361 *See generally* Gabrielle Kaili-May Liu, 'Perspectives on the Social Impacts of Reinforcement Learning with Human Feedback' (2023) arXiv preprint 1 <https://arxiv.org/pdf/2303.02891.pdf> accessed 17 July 2024. Within the recent field of RLHF, the so-called Reinforcement Learning with Heuristic Imperatives (RLHI) methods deserve at least a mention. The latter address the control problem in the context of LLMs with the objective to align Generative AI models to ethical requirements. *See* David Shapiro and others, 'Reinforcement Learning with Heuristic Imperatives (RLHI)' (*GitHub*, 2023) <https://github.com/daveshap/RLHI> accessed 17 July 2024.

362 *See, e.g.*, Peer Nagy and others, 'Generative AI for End-to-End Limit Order book Modelling: A Token-Level Autoregressive Generative Model of Message Flow Using a Deep State Space Network' (2023) arXIv preprint 1 <https://doi.org/10.48550/arXiv.2309.00638> accessed 17 July 2024.

this dissertation intentionally does not delve into the specifics of this AI development, focusing on RL as the main ML paradigm of analysis.

The role of the human factor as a conducive element for the inducing manipulation by autonomous AI to occur deserve a closer look. Mostly, it remains to be seen to what extent human input is necessary to guide AI trading agents in discovering manipulation as an optimal strategy, especially in real market contexts. For instance, humans can encourage AI to circumvent market conduct rules through training with empirical data or providing feedback during live trading operations. In both cases, the human factor is strictly responsible for guiding AI towards market misconduct. Therefore, one must refrain from properly speaking of autonomous manipulation by AI *per se* in these circumstances. However, consciously deploying AI trading for implementing manipulative strategies can still be challenging, mainly due to practical and technical limitations that trading agents may encounter in real markets.[363] Additionally, since successful attempts to manipulate markets usually involve high costs and risks before a strategy can materialise into profit,[364] investing substantial resources to develop manipulative AI trading systems may not always be worth all the associated financial and time commitments. Beyond mere financial risks, malicious use of AI also entails operational, legal, and reputational risks for their perpetrators.

Overall, in light of ongoing advancements in the field of 'Deep Computational Finance', it is reasonable to believe that specific ML methods—such as RL and DRL—can offer malicious actors a broader range of opportunistic strategies to evade market conduct rules. Moreover, artificial trading agents that leverage RL methods may also

363 *Cf.* Sun, Wang, and An (n 196) 20-22.

364 Daniel R Fischel and David J Ross, 'Should the Law Prohibit "Manipulation" in Financial Markets?' (1991) 105 Harvard Law Review 503 <https://www.jstor.org/stable/1341697> accessed 17 July 2024, who argue that the law should rule out the prohibition of trade-based market manipulation. This is mainly because it is notoriously difficult to distinguish illegal trading conduct from legitimate trading activity. Moreover, any attempt at market manipulation can generally lead to uneconomic outcomes for the perpetrators.

open up to novel scenarios in which market manipulation occurs as an autonomous decision of AI trading systems, regardless of specific human intent. Below, we examine from a conceptual perspective some of these risks through a series of case studies.

3.4 Case Studies

AI trading may optimise known forms of market manipulation or bring forth new ones. One prominent area in which AI applications have demonstrated significant impact, whether for good or bad, is the proprietary HFT industry. The huge amounts of market microstructure data generated by HFT markets at astonishing speeds can, in principle, be readily exploited by ML-based trading strategies, even for illicit purposes. While HFT is undoubtedly a fertile field for ML research and practice, it is not the only domain of application in algorithmic trading. AI trading systems can also be applied in less speedy, less interconnected, and less transparent markets.

Without pretending to provide an exhaustive list, in the following we examine several illustrative scenarios in which ML-based trading strategies may engage in manipulative market behaviours with increasing autonomy.[365] This list includes:

(A) *deceptive* trading strategies, like 'spoofing';[366]

365 Very little indeed is known about new and emerging algorithmic forms of market manipulation. Putniņš (n 20) 35-37, according to which market manipulation by autonomous AI trading will raise new fundamental legal questions for financial regulation.

366 The term 'spoofing' refers to manipulative practices involving the submission and cancellation of trading orders without the real intention of execution with the effect of misleading other market participants as to the natural trading interest in a specific financial instrument. *See, e.g.*, Lin (n 70) 1289; *see also* Scopino (n 70) 648-654, who discusses recent developments on the legal treatment of spoofing by US regulators and courts.

(B) *aggressive* trading strategies, such as 'pinging'[367] and 'momentum ignition'[368];

(C) *cross-asset* and *cross-market* manipulation; and

(D) '*hybrid*' manipulative strategies, combining elements from various strategies including information-based manipulation, which leverages the crucial role of information in financial decision-making.

A. Deceptive strategies

Those strategies that aim to deceive other market participants through the rapid submission and cancellation of orders (such as 'spoofing')—commonly known as 'order-based manipulation'[369]—would seem ideal targets for optimisation by AI trading.[370] These '*deceptive*' strategies are somewhat constrained by 'order-to-trade ratio' (OTR) rules imposed by trading venues, which are designed to discourage algorithmic traders from engaging in *non-bona fide* trading practices.

The main challenge to fight these manipulative strategies lies in the inherent difficulty to effectively differentiate them from other legitimate trading practices (e.g., market making). This is mainly because high rates of order submission, cancellation, and modification do not necessarily conceal malicious intent, but can also be justified

367 'Pinging' refers to the strategy of placing small tradable orders to discover the presence of large hidden orders resting in deeper levels of electronic order books in a dark pool or exchange.

368 'Momentum refers to manipulative practices involving several trading orders with the aim of initiating or inflating a price trend on a financial instrument in order to encourage other market participants to trade in the same direction before opening/closing a position on more favourable terms.

369 *See* Viktoria Dalko and Michael H Wang, 'High-Frequency Trading: Order-Based Innovation or Manipulation?' (2020) 21 Journal of Banking Regulation 289 <https://doi.org/10.1057/s41261-019-00115-y> accessed 17 July 2024.

370 *E.g.*, Martínez-Miranda and others (n 344); Wellman and Rajan (n 344) 619-620; Lopez de Prado (n 161) 293-294; Mizuta (n 327); OECD (n 135) 27-28; Byrd (n 344).

by legitimate reasons such as changing market conditions or other economic factors.[371] Consequently, identifying and addressing order-based forms of market manipulation is usually a complex task for enforcement bodies,[372] especially when these practices involve cross-asset and/or cross-market trading activity.[373]

In spite of the limitations imposed by OTR rules, it is possible to argue that AI trading can optimise and even autonomously discover deceptive strategies such as 'spoofing'. For instance, recent studies based on in-lab market simulations have revealed the ability of RL trading agents to autonomously develop a tendency, through self-learning, to identify and exploit vulnerabilities in market functioning.[374] Specifically, RL-based agents can interact with order books by sending bogus orders in order to discover and thus exploit manipulative trading strategies. Thus, these agents are able to maximise profits by leveraging market microstructure information,[375] as an optimal and rational market behaviour.[376]

Recent empirical research by *Cartea and others (2023)* introduces a dynamic model for decision-making of RL trading algorithms that learn optimal strategies. The authors also derive testable conditions to determine the manipulation potential of a given algorithm.[377] In particular, they found that in circumstances when market makers can afford bearing inventory risk, their trading algorithms can self-learn how to

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371 *Cf.* Xuan Tao and others, 'On Detecting Spoofing Strategies in High-Frequency Trading' (2021) Quantitative Finance 2 <https://doi.org/10.1080/14697688.2022.2059390> accessed 17 July 2024.

372 *See* footnotes n. 78-83 and accompanying text.

373 *See* Joseph Zabel, 'Rethinking Open- and Cross-Market Manipulation Enforcement' (2021) 15 Virginia Law & Business Review 417 <https://ssrn.com/abstract=3682103> accessed 17 July 2024.

374 *See, e.g.*, Martínez-Miranda and others (n 344); Byrd (n 344).

375 Ibid.

376 Ibid.

377 *See* Álvaro Cartea and others, 'Spoofing Order Books with Learning Algorithms' (2023) SSRN preprint 1 <https://ssrn.com/abstract=4639959> accessed 17 July 2024.

develop spoofing-based strategies. According to their model, the authors show the twofold purpose of 'spoofing': (*i*) the optimisation of inventory mean reversion, and (*ii*) the execution of round-trips trades with limit orders at a higher probability.[378] In the face of these risks, AI trading thus poses additional complexities for market conduct regulators in effectively overseeing and regulating market activities.

B. Aggressive strategies

AI trading may also find profitable application in '*aggressive*' HFT strategies such as 'pinging' or 'momentum ignition'.[379] In the context of 'pinging', for example, the aim of a manipulator is to detect hidden resting orders on books by 'pinging' markets in the quest for liquidity.[380] Therein, RL-based agents could obtain strategic information through the mere observation of market price dynamics to the point of developing some understanding of the trading strategies adopted by their competitors. Thanks to this knowledge, RL trading agents could hence actively search for hidden liquidity and even predict the forthcoming orders of other traders.[381] These strategies could also be employed during monetary policy announcements or open market operations conducted by central banks, potentially interfering with the effectiveness and efficiency of the latter.[382]

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378 Ibid.

379 *See, e.g.*, Martínez-Miranda and others (n 344); *see also* Scopino (n 70) 626, quoting the US SEC defining these strategies as "parasitic".

380 Scopino (n 70) 622-626, arguing that high speed 'pinging', which basically relies on high levels of order submission and cancellation, should be made illegal because it provides no real benefit to market efficiency.

381 *Cf.* Nicholas Hirschey, 'Do High-Frequency Traders Anticipate Buying and Selling Pressure?' (2021) 67(6) Management Science 3321, 3343 <https://doi.org/10.1287/mnsc.2020.3608> accessed 17 July 2024 who find evidence of a so-called "anticipatory" trading channel allowing HFT to act faster than other market participants, thus resulting in higher costs for the latter; Dalko and Wang (n 369) 293-294, arguing that HFT market making strategies can enjoy a time advantage relative to other market participants.

382 *Cf.* Lee Smales and Nicholas Apergis, 'Understanding the Impact of Monetary Policy Announcements: The Importance of Language and Surprises' (2017) 80 Journal of Banking and Finance 33, 34-35 <https://doi.org/10.1016/j.jbankfin.2017.03.017> accessed 17 July 2024. According

In 'momentum ignition' strategies, instead, the goal of a manipulator is to anticipate and initiate a sudden price trend in order to attract other algorithmic traders to engage in trading the same asset(s).[383] Even in this context, AI trading has the potential to optimise forms of market manipulation. Actually, there is a growing body of research in Computational Finance dedicated to the art of deciphering and anticipating price trends by observing market dynamics through ML methods.[384] While these methods could potentially be misused by malicious actors to implement aggressive trading strategies, they could also inadvertently lead to market manipulation by AI trading. Indeed, recent studies show that ML methods can be leveraged to execute sophisticated manipulative HFT strategies, thanks to a thorough understanding of the IT infrastructure of trading platforms and/or the underlying economic mechanics of market microstructure.[385]

to the authors, monetary policy announcements are often followed by a noticeable increase in trading volume and market volatility. Even when liquidity is reduced in the presence of hard-to-interpret announcements for market participants, trading volume remains relatively high. One possible explanation for this phenomenon is that certain traders may possess an information processing advantage that allows them to offset the higher trading costs.

383 SEC, 'Concept Release on Equity Market Structure' (14 January 2010) Exchange Act Release No. 34-61358, File No. S7-02-10, RIN 3235-AK47 56-57 <https://www.sec.gov/files/rules/concept/2010/34-61358.pdf> accessed 17 July 2024.

384 *See, e.g.*, Jun Chen and Edward PK Tsang, *Detecting Regime Change in Computational Finance: Data Science, Machine Learning and Algorithmic Trading* (Chapman and Hall/CRC Press, 2021) xix, whose authors consider their book "*an attempt to push forward in the field of financial analysis, using new ways to engage with financial data, under our chosen method of Directional Change, and harnessing some of the cutting-edge tools of machine learning and the related algorithmic trading*."

385 *Cf.* Vasilios Mavroudis, 'Market Manipulation as a Security Problem' in *EuroSec '19: Proceedings of the 12th European Workshop on System Security* (ACM 2019) 1-6 <https://dl.acm.org/doi/10.1145/3301417.3312493> accessed 17 July 2024, which refers to these forms of manipulative strategies as 'mechanical arbitrage' techniques and discusses the role of both technical and regulatory countermeasures in reducing the phenomenon.

C. Cross-asset and cross-market manipulation

In increasingly interconnected yet fragmented global capital markets, novel forms of market manipulation that transcend the silos inherent to control mechanisms has emerged. These include '*cross-asset*' and '*cross-market*' manipulative strategies.[386]

Thanks to enhanced analytical and computational capabilities, AI trading has the potential to achieve a ubiquitous presence in the markets, allowing for simultaneous monitoring of various financial assets even across multiple trading venues.[387] Moreover, financial engineering also appears to broaden the manipulative prospects for AI trading, offering opportunities for 'cross-asset' manipulation. For instance, as derivative products derive their pricing from other underlying financial assets, AI may find ways to optimise strategies aimed at manipulating the price of underlying assets in order to accumulate profits in financial positions related to corresponding derivatives.[388] In the realm of financial benchmark, for instance, scientific studies based on in-lab experiments show that RL-based trading agents possess the capacity to autonomously discover and engage in market manipulation, irrespective of human intent.[389]

D. 'Hybrid' forms of manipulation

Even more sophisticated manipulative strategies may become available to AI trading. Particularly, this can be the case of so-called 'hybrid' forms of market manipulation,

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386 *See, e.g.*, IOSCO (n 313); *see also* Yadav (n 126), arguing that "*algorithmic trading has thickened interconnections across venues and asset classes. Algorithmic traders can transact across multiple platforms . . . to engage in arbitrage-related strategies or to make markets.*"

387 *See, e.g.*, Zabel (n 373) 464, who examines how algorithmic trading undermines the ability of prosecutors to regulate and enforce against cross-market manipulation strategies.

388 *See* Andrew Verstein, 'Benchmark Manipulation' (2015) 56(1) Boston College Law Review 215, 217 and 250 <https://bclawreview.bc.edu/articles/543> accessed 17 July 2024, arguing that derivatives and other financial benchmarks are becoming increasingly targets of manipulative strategies, given their economic function as a reference value for pricing other financial assets.

389 *See* Shearer, Rauterberg, and Wellman (n 344); Barr and others (n 344).

which combine various elements of the manipulative practices mentioned above as well as other ones. In this last regard, we could envision scenarios where AI trading engage in unlawful practices that extend beyond conventional forms of trading-based manipulation. One such example might be strategies involving 'information-based' manipulation[390], which exploits the role of media technology,[391] including social media platforms.[392] These risks are well evidenced, for instance, by the so-called *GameStop* saga. In that case, through information shared on the social media platform *Reddit*, an undefined group of retail investors allegedly caused a stock price hike for the US company, considered one of the world's largest retailers of video games as well as board game.[393]

The cyberspace of the Internet may indeed serve as a catalyst for manipulation as it provides a relatively easy, cost-effective, and efficient means of disseminating misleading information. In turn, these fake news disseminating activities may in fact be used to intentionally influence the prices of financial products or create a semblance

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390 The term 'information-based' manipulation generally refers to manipulative strategies based on the dissemination of false information or the spreading of false rumours. Franklin Allen and Douglas Gale, 'Stock-Price Manipulation' (1992) 5(3) The Review of Financial Studies 503, 505 <https://doi.org/10.1093/rfs/5.3.503> accessed 17 July 2024.

391 *See, e.g.*, Lin (n 70) 1292-1294, speculating on the emergence of audacious and innovative manipulative schemes aimed at distorting market prices by disseminating false information via digital media; Consulich and others (n 106) 57-58, arguing that AI could produce a disruptive expansion of possible information manipulation strategies, exploiting, for example, the phenomenon of apps that produce fake news with the support of human images or voices, making the false information offered extremely realistic to the public.

392 For two empirical studies demonstrating the role of social media as a mean for malicious actors to spread false or misleading information in order to carry out manipulative trading strategies, see Thomas Renault, 'Market Manipulation and Suspicious Stock Recommendations on Social Media' (2017) SSRN preprint 1 <https://ssrn.com/abstract=3010850> accessed 17 July 2024; Shimon Kogan, Tobias J Moskowitz, and Marina Niessner, 'Social Media and Financial News Manipulation' (2023) 27(4) Review of Finance 1129 <https://doi.org/10.1093/rof/rfac058> accessed 17 July 2024.

393 *See* Maggie Sklar, '"YOLOing the Market": Market Manipulation? Implications for Markets and Financial Stability' (2021) Policy Discussion Paper Series DP-2021-01, Federal Reserve of Chicago <https://www.chicagofed.org/-/media/publications/policy-discussion-papers/2021/pdp-2021-01-pdf.pdf> accessed 17 July 2024; Henry David Gale, '"Buy GameStop!": The Need to Rethink the Approach to Market Manipulation in a WallStreetBets World' (2023) 108 Iowa Law Review 1923 <https://ilr.law.uiowa.edu/sites/ilr.law.uiowa.edu/files/2023-05/N2_Gale.pdf> accessed 17 July 2024.

of interest in them.[394] Hence, whether explicitly programmed and trained by human experts or even in the course of autonomous activity, AI systems may result in forms of 'information-based manipulation'. By observing and interacting with social media content or other relevant media platforms, AI trading agents may attempt to mislead other market participants, including rival news-reading algorithms.[395]

3.5 Conclusion

In light of the rapid advancements in ML research applied to financial trading, this chapter has focused on the dark side of AI trading: its potential for market manipulation. We first emphasised the importance of protecting market integrity against market manipulation, especially considering the additional risks introduced by technological innovation in financial trading. And, indeed, the widespread adoption of AI in trading can be expected to significantly amplify the risks of manipulative practices in the market.

We introduced a basic analytical framework to examine the phenomenon of market manipulation by AI trading, mainly to measure the varying degree of human involvement. Our framework identifies four distinct scenarios wherein AI trading can cause market disruption, distortion, and harm. Each scenario involves different levels of human involvement: (1) operational vulnerability (i.e. 'AI as a victim'), (2) 'traditional unintended consequences', (3) 'conscious misuse by humans', and (4) 'autonomous misconduct by AI trading'.

It is worth acknowledging that AI trading can be involved in both old and new forms of market manipulation. Despite certain manipulative strategies historically

394 *See* IOSCO (n 20) 2-3.

395 *See* Bathaee (n 76) 911-913, who provides an illustrative example on AI agents engaging in 'paint-the-tape' manipulative strategies by posting content on social media, like Twitter or Facebook, in order to deceive other market participants; Consulich and others (n 106) 57-58 and 61-63.

deemed challenging or financially risky to implement,[396] the optimisation capability offered by AI may alleviate many of these practical constraints. Nevertheless, our primary focus is identifying the novel risks of market manipulation by autonomous AI trading—an area posing greater complexities for regulatory bodies and enforcement authorities. From a conceptual perspective, we thus discussed how, thanks to ML, AI trading might optimise sophisticated manipulative strategies, even in the HFT domain. By contrast, we also highlighted a number of practical and technical limitations that may ultimately preclude market manipulation by autonomous AI systems in real markets.

Supported by insightful case studies and burgeoning evidence from in-lab research in the fields of Computational Economics and Computational Finance, our analysis suggests that AI agents could acquire the ability to engage with various forms of market manipulation without specific human intent (e.g., via programming or other instruction). Therefore, the idea that ML-based trading agents may surpass the intelligence of their developers and users, independently discovering methods for market manipulation in pursuit of pre-defined objectives (i.e. some sort of profit maximisation function under some risk control), seems more than mere speculation or fiction. It presents itself as a possible reality, at least from a techno-methodical standpoint.

Overall, our findings compel us to acknowledge the additional and emerging risks to market integrity associated with specific ML methods—i.e. those grounded in (D)RL—that allow the establishment of increasingly capable and autonomous artificial trading agents. In the next chapter, we will delve deeper into these risks, exploring the prospects of AI trading agents potentially coordinating their behaviour with their market competitors, thereby exposing markets to outcomes akin to collusive behaviour.

396 *See* footnote n. 364.

4. TACIT COLLUSION BY AUTONOMOUS AI TRADING

If the previous chapter has dealt with the emerging risks of market manipulation introduced by AI-powered trading systems, this chapter goes a step further to explore 'collective' forms of market abuse—typically known as 'collusion'—in markets increasingly dominated by algorithmic agents.

This research focus is primarily motivated by growing concerns, particularly among Competition Law scholars and authorities, regarding algorithmic-enabled forms of collusion. Specifically, our investigation delves into *whether* and *effectively how* competing trading agents, powered by ML, might autonomously engage in collusive-like behaviours—commonly termed 'algorithmic tacit collusion'.[397] To the

[397] Within the Competition Law scholarship, there are growing concerns about the potential of AI-based pricing agents to facilitate anti-competitive behaviour among competing firms. *See* Salil K Mehra, 'Antitrust and the Robo-Seller: Competition in the Time of Algorithms' (2016) 100 Minnesota Law Review 1323 <https://www.minnesotalawreview.org/wp-content/uploads/2016/04/Mehra_ONLINEPDF1.pdf> accessed 17 July 2024, who discusses how pricing algorithms have impacted market dynamics and how increased autonomy in algorithmic decision-making poses challenges to traditional competition law concepts and enforcement. While all these studies highlight the risks of algorithmic collusion in various industries, there is very limited research specifically addressing the risk of algorithmic 'tacit' collusion in capital markets; Ariel Ezrachi and Maurice E Stucke, 'Artificial Intelligence & Collusion: When Computers Inhibit Competition' (2017) 2017 University of Illinois Law Review 1775 <https://illinoislawreview.org/wp-content/uploads/2017/10/Ezrachi-Stucke.pdf> accessed 17 July 2024, exploring four different scenarios where AI can foster collusion, including what the authors' term as the 'Digital Eye', the scenario in which collusion arises from autonomous AI decision-making as a rational strategy; Joseph E Harrington, 'Developing Competition Law for Collusion by Autonomous Artificial Agents' (2018) 14(3) Journal of Competition Law and Economics 331 <https://doi.org/10.1093/joclec/nhy016> accessed 17 July 2024, who examines the limitations of current regulatory regimes to regulate forms of collusion between algorithms; Michal S Gal, 'Algorithms as Illegal Agreements' (2019) 34(1) Berkeley Technology Law Journal 67 <https://doi.org/10.15779/Z38VM42X86> accessed 17 July 2024, who rebuts the claim that current laws are adequate to address forms of coordination facilitated by algorithms; Alena Spridinova and Edvardas Juchnevicius, 'Price Algorithms as a Threat to Competition Under the Conditions of Digital Economy: Approaches to Antimonopoly Legislation of BRICS Countries' (2020) 7(2) BRICS Law Journal 94 <https://doi.org/10.21684/2412-2343-2020-7-2-94-117> accessed 17 July 2024, who stresses the need for regulators worldwide to adopt a common approach to regulate the use of algorithms in digital markets; Lea Bernhardt and Ralf Dewenter, 'Collusion by Code or Algorithmic Collusion? When Pricing Algorithms Take Over' (2019) 16(2-3) European Competition Journal 312 <https://doi.org/10.1080/17441056.2020.1733344> accessed 17 July 2024, who, while considering collusion between algorithms an exaggerated risk for the time being, believe there is room for improvement in current enforcement regimes; Salil K Mehra, 'Price Discrimination-Driven Algorithmic Collusion: Platforms for Durable Goods' (2021) 26(1) Stanford

best of the author's knowledge, this dissertation stands as a pioneering endeavour within the legal research community to address, in-depth and breath, the risks of 'algorithmic tacit collusion' in capital markets associated with specific ML methods—particularly DRL.[398]

In addressing the phenomenon of algorithmic collusion in capital markets, this chapter proceeds as follows. First, we provide a conceptualisation of capital markets, including their socio-economic and institutional aspects, as possible targets of collusive practices. This requires us to recognise the transformative role of technology—such as AI, algorithms, and ICT infrastructures and components—and its impact on market functioning, particularly the behaviour and interaction of market participants. This first conceptualisation will allow us to discover the central role of the concept of 'algorithmic interconnectedness' in researching the new risks of collusion associated with AI (Chapter 4.1). Moving forward, we address the role played by algorithms in facilitating collusion in digital markets. Here, we introduce two primary concepts:

(i) the deliberate (mis)use of algorithms by competing firms to achieve strategic coordination better (i.e. technology-enabled 'explicit' collusion); and

Journal of Law, Business & Finance 171 <https://heinonline.org/HOL/P?h=hein.journals/stabf26&i=177> accessed 17 July 2024, who examines risks of algorithmic forms of collusion in digital platforms; Francisco Beneke and Mark-Oliver Mackenrodt, 'Remedies for Algorithmic Collusion' (2021) 9(1) Journal of Antitrust Enforcement 152 <https://doi.org/10.1093/jaenfo/jnaa040> accessed 17 July 2024, who focus on the role of fines and other remedies to discourage the occurrence of collusive behaviour; Cary Coglianese and Alicia Lai, 'Antitrust by Algorithm' (2022) 2(1) Stanford Computational Antitrust 1 <https://law.stanford.edu/wp-content/uploads/2022/03/Coglianese-Lai.pdf> accessed 17 July 2024, who argue that market regulators will need to make greater use of AI and data analytics technologies to ensure the effective enforcement of market conduct regulations.

398 In this sense, this dissertation represents a first original attempt to bridge different scientific disciplines, namely Competition Law, Computational Economics and Antitrust, Computational Finance and Financial Regulation.

(ii) the emergence of autonomous algorithms capable of achieving collusive outcomes without explicit human intent, known as algorithmic 'tacit' collusion (Chapter 4.2).

Following this, we probe those key market factors that, according to economic theory, could foster collusion. While not purporting to be exhaustive, our examination covers fundamental factors such as: (A) 'market transparency', (B) 'frequency of interactions', (C) 'product homogeneity', (D) 'market concentration', (E) 'entry barriers and innovation', and (F) 'their combined effect' (Chapter 4.3). We then explore the relationship between RL and algorithmic collusion, providing an overview of both theoretical, empirical, and experimental scientific literature. This discussion allows us to substantiate the risks RL-based trading agents pose in engaging in collusive behaviour, considering both technical and practical limitations faced by competing algorithms within real market conditions. Additionally, we highlight the challenges for regulatory frameworks and market integrity introduced by AI trading (Chapter 4.4.). Furthermore, we present two case studies—involving 'quote-driven markets' and 'financial benchmarks'—to illustrate potential scenarios of algorithmic 'tacit' collusion within specific segments of capital markets. By considering both market micro-structure elements and the technical aspects/limitations of specific ML methods, particularly RL, we also seek to evaluate the likelihood of the unprecedented risk of 'tacit' collusion by competing trading algorithms (Chapter 4.5.). Eventually, the chapter concludes with a summary and final remarks (Chapter 4.6.).

4.1 Algorithmic Interconnectedness and 'Tacit' Collusion

The financial services industry is not immune to collective forms of market abuse.[399] Prominent recent cases, such as the LIBOR scandal and the manipulation of foreign

[399] Since Modern times, the business world, and particularly capital markets, have historically been susceptible to various forms of abuse and manipulation, including collusive agreements, carried out by unscrupulous actors. One of the earliest accounts of how capital markets have been subject to speculation and various market abuses can be found in Joseph Penso de la Vega, *Confusión de*

exchange (FX) currency markets, are vivid reminders of the threats and vulnerabilities to which global capital markets are exposed.[400] Indeed, both of these examples underscore the alarming risks of collusion between human traders and high finance professionals in order to exploit the system for personal gain. While the use of technology can generally facilitate humans to establish and sustain cartel agreements more effectively,[401] the proliferation of AI trading systems in capital markets may have several implications for competition in the industry.[402]

In both scientific and regulatory circles, there is a growing concern about the risks of herding behaviours and one-way markets arising from competing AI pricing agents in digital marketplaces. These concerns, although still in their early stages and rather constrained, highlight the potential challenges and implications associated with

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Confusiones: Dialogos curiosos entre un philosopho agudo, un mercante discrete y un accionista erudite descrivendo el negocio de las acciones, su origen, su ethimologia, su realidad, su juego e su enredo (Amsterdam 1968), of which only a partial translation in English exists: Joseph Penso de la Vega, *Confusión de confusions [1968]: Portions Descriptive of the Amsterdam Stock Exchange* (Hermann Kellenbenz tr, Baker Library, Harvard Graduate School of Business Administration 1957) <https://gwern.net/doc/economics/1688-delavega-confusionofconfusions.pdf> accessed 17 July 2024.

400 In the EU, both scandals led several large global banks to record fines imposed by the European Commission. For the prosecution of the LIBOR case by EU Competition Law authority, see European Commission, 'AMENDED - Antitrust: Commission Fines Banks € 1.49 Billion for Participating in Cartels in the Interest Rate Derivatives Industry' (4 December 2013) Press Release, IP/13/1208 <https://ec.europa.eu/commission/presscorner/detail/en/IP_13_1208> accessed 17 July 2024 Following further investigations, the European Commission then extended its sanctions to other institutions. *See* European Commission, 'Antitrust: Commission fines Crédit Agricole, HSBC and JPMorgan Chase € 485 Million for Euro Interest Rate Derivatives Cartel' (7 December 2016) Press Release, IP/16/4304 <https://ec.europa.eu/commission/presscorner/detail/it/IP_16_4304> accessed 17 July 2024. For the prosecution of the FX scandal, instead, see European Commission, 'Antitrust: Commission Fines Barclays, RBS, Citigroup, JPMorgan and MUFG €1.07 Billion for Participating in Foreign Exchange Spot Trading Cartel' (16 May 2019) Press Release, IP/19/2568 <https://ec.europa.eu/commission/presscorner/detail/en/IP_19_2568> accessed 17 July 2024. Further investigations into the FX scandal have more recently led to other sanctions. *See* European Commission, 'Antitrust: Commission Fines UBS, Barclays, RBS, HSBC and Credit Suisse € 344 Million for Participating in a Foreign Exchange Spot Trading Cartel' (2 December 2021) Press Release, IP/21/6548 <https://ec.europa.eu/commission/presscorner/detail/en/ip_21_6548> accessed 17 July 2024.

401 *See, e.g.*, Ezrachi and Stucke (n 397); OECD, 'Algorithmic Competition: OECD Competition Policy Roundtable Background Note' (2023) 13-16 <http://www.oecd.org/daf/competition/algorithmic-competition-2023.pdf> accessed 17 July 2024.

402 *See generally* OECD (n 135) 9-10 and 40.

AI for competition in these market environments. Notably, independent AI systems competing in markets may lead to cartel-like outcomes in novel and unprecedented ways.[403] While in the past, collusive parties needed to rely on some form of communication to coordinate their market behaviour, delegating cognitive tasks and strategic decision-making to AI may open up new avenues for collusion to occur that do not necessarily require explicit communication between rivals: i.e. the phenomenon of 'tacit' collusion.[404] Thanks to superior analytical capabilities offered by specific ML methods, rival AI agents might potentially converge strategic behaviour without direct communication and achieve sub-optimal market equilibria to the detriment of other market participants and consumers.[405]

Hence, given the increasing prevalence of AI trading algorithms in contemporary and future capital markets, there is a need to scrutinise their transformative impact on the competitive landscape and to assess the likelihood of risks of algorithmic collusion, parallel to those observed in other sectors of the economy, materialising in this domain as well. At least from a normative perspective, we should not forget that financial technology and innovation must ultimately align with broader public goals such as economic prosperity, sustainability, financial stability, financial resiliency, and market integrity, among others. Under this perspective, therefore, evaluating possible risks of algorithmic collusion to occur in capital markets is timely and relevant. As will be seen, although there may be various techno-practical barriers impeding the concrete emergence of algorithmic-based forms of collusion, recent studies indicate that under specific techno-economic conditions,

403 *See generally* OECD (n 21) 18-32; *see also* Mehra (n 397) 1368-1373, overviewing some of the most recent contributions by competition law scholars.

404 *See, e.g.*, Ezrachi and Stucke (n 397) 1795-1796; OECD (n 401) 13-15; *but see* Luca Calzolari, 'The Misleading Consequences of Comparing Algorithmic and Tacit Collusion: Tackling Algorithmic Concerted Practices Under Art. 101 TFEU' (2021) 6(2) European Papers 1193 <https://www.europeanpapers.eu/fr/system/files/pdf_version/EP_eJ_2021_2_6_Articles_Luca_Calzolari_00519.pdf> accessed 17 July 2024.

405 For a reference to the most influential literature on the subject, see footnote n. 397.

AI-enabled forms of collusion are at least theoretically feasible. Thus, the forthcoming sections of this chapter aim to explore these factors in greater detail.

4.2 Algorithms as Facilitators for Collusion

Malicious market players are constantly in search of more effective and efficient techniques to carry out illicit activities. Therefore, it should not come as a surprise that humans may seek innovative technological solutions, such as the use of algorithms, to engage in forms of market abuse, including cartel agreements.

Cartel agreements between rival firms can take various forms, including colluding to set prices, control output, or create other barriers to natural competition.[406] Because of their detrimental effects on social welfare, all these activities are deemed illegal in most jurisdictions worldwide.[407] However, forming cartels presents several strategic difficulties and risks for competing firms. The main challenges include maintaining secrecy among cartel members, ensuring commitment to the agreed-upon terms, and preventing defection from collusive behaviours. Additionally, cartel agreements face the risk of detection and severe legal and reputational consequences, such as hefty fines and criminal prosecution.[408] These challenges and risks make the formation and sustenance of cartels a complex and risky undertaking for rival firms.

In digital marketplaces, however, algorithms have the potential to relax many of the constraints traditionally faced by competing firms to achieve collusive

406 *E.g.*, OECD (n 21) 19-20.

407 For a chronicle of competition law instruments activated in various world jurisdictions, see Anu Bradford and others, 'Competition Law Gone Global: Introducing the Comparative Competition Law and Enforcement Database' (2019) 16(2) Journal of Empirical Legal Studies 411 <https://doi.org/10.1111/jels.12215> accessed 17 July 2024.

408 For an introduction to the economics of cartel formation, duration, and stability, see John Asker and Volker Nocke, 'Collusion, Mergers, and Related Antitrust Issues' 5(1) Handbook of Industrial Organization 177 <https://doi.org/10.1016/bs.hesind.2021.11.012> accessed 17 July 2024.

agreements.[409] In particular, algorithm-driven markets may facilitate strategic coordination thanks to enhanced market transparency and accelerated frequency of interactions among market participants. These aspects, in turn, can render cartel monitoring and retaliation against those who deviate from the collusive terms significantly more cost-effective.[410]

It is important to note that the mere use of algorithms as tools to better accomplish collusion does not create *per se* new legal problems for enforcement authorities, established that there is an explicit cartel agreement among the colluding parties *a priori*. In such cases, in fact, algorithms simply serve as facilitating instruments for establishing cartel agreements. Thus, despite common problems related to evidentiary burden of proof, regulators can still largely rely on traditional legal concepts and rules in their enforcement actions.[411] However, whenever algorithms are employed to facilitate explicit forms of collusion, law enforcement agencies face a number of complications. These are mainly due to the difficulty of assessing the likelihood of these cases occurring, ensuring their detection and, finally, attributing liability to specific human actors.[412] Further complicating matters is the fact that market interactions between competing algorithms may lead to unintended consequences for which it may be difficult to blame specific actors. This risk is particularly evident in the context of capital markets, given all sort of possible ways in which trading algorithms interact.[413] Moreover, as algorithms grow in complexity and

[409] *See, e.g.*, Gal (n 397) 71.

[410] *See, e.g.*, Ariel Ezrachi and Maurice E Stucke, 'Tacit Collusion on Steroids – The Tale of Online Price Transparency, Advance Monitoring and Collusion' (2017) 3(2) Competition Law & Policy Debate 24, 28 <https://ir.law.utk.edu/utklaw_facpubs/200> accessed 17 July 2024.

[411] *See, e.g.*, Ezrachi and Stucke (n 397) 1784-1796, arguing that the safe application of competition law's traditional enforcement concepts and tools may ultimately depend on the precise scope of application of a given algorithm as a collusive device as well as its actual level of sophistication.

[412] *See, e.g.*, OECD (n 403) 33.

[413] *See, e.g.*, ibid 24-26, referring to the May 2010 Flash Crash in US stock markets to highlight the risks introduced by algorithms.

autonomy, law enforcement mechanisms and tools must keep pace with market and technological developments to maintain their effectiveness.[414]

While being an intriguing research area in disciplines like Computational Economics and Financial Sociology, in-depth investigation about the market effects resulting from the interactions between competing trading algorithms—except for general systemic risk concerns—has not received substantial attention from both financial regulators and legal scholars.[415] From a sociological perspective, for instance, the advent of algorithms as the new protagonists in the trading floor scene has undeniably influenced the collective behaviour of capital markets. Contemporary trading venues are awash with competing trading algorithms that interact and communicate by observing and populating electronic order books.[416]

Conversely, the legal scholarship has not yet fully devoted its attention to investigating the exact properties and mechanisms characterising algorithmic trading interconnectedness, particularly its collusive potential, as well as the resulting implications for financial regulation.[417] This knowledge gap represents a dangerous scientific limitation because the possible adverse consequences due to algorithm interactions, especially the risk of collusion-like behaviour, remain under-explored.[418]

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414 *See, e.g.*, OECD (n 403) 39; Ezrachi and Stucke (n 397) 256-257.

415 While concerns about the systemic risks introduced by algorithms in capital markets have received a fair amount of attention, specific investigations into the risks of algorithm-enabled forms of collusion have been significantly underexplored. As highlighted in this chapter, however, it is noteworthy that academic research is increasingly turning its attention to this area.

416 *See generally* Donald MacKenzie, 'How Algorithms Interact: Goffman's "Interaction Order" in Automated Trading' (2019) 36(2) Theory, Culture & Society 39 <https://doi.org/10.1177/0263276419829541> accessed 17 July 2024, who illustrates two so-called Goffmanesque aspects of algorithmic interaction in capital markets trading, namely 'queuing' and 'spoofing'.

417 As an exception, albeit with a focus on market manipulation and not collusion, only a couple of interdisciplinary studies between Computer Science and Financial Law stand out, including Shearer, Rauterberg, and Wellman (n 344) and Barr and others (n 344).

418 *See generally* OECD (n 403) 34-36, highlighting the many challenges algorithms present for both competition law enforcement and market regulation; *see also* Ariel Ezrachi and Maurice E Stucke,

In principle, AI trading may introduce risks of both 'explicit' and 'tacit' forms of collusion. As for the case of the LIBOR or FX fixing scandals mentioned before, 'explicit' collusion involves direct communication or coordination between rivals to manipulate prices or control market outcomes. Conversely, 'tacit' collusion arises when competing firms independently learn similar strategies and behaviours, leading to parallel actions that adversely impact market dynamics.[419] While AI may facilitate malicious human actors to implement white-collar crimes, our focus here is on understanding whether and how independent trading algorithms may alter the competitive dynamics in capital markets.

Due to ML, AI trading applications become increasingly sophisticated and capable; this prompts us to begin examining the possible impact on competition in capital markets as these systems will become widely deployed. With self-learning capabilities, competing AI trading agents—particularly those based on RL methods—may find ways to coordinate their market behaviour.[420] This coordination could occur without explicit instruction from the human developers and users, as AI seeks to optimise its pre-set business goal—most likely some sort of profit maximisation under risk control.[421] In this new and unprecedented scenario, falling under the category of 'market misconduct by autonomous AI', two or more independently employed AI trading agents from competing firms would possess sufficient capabilities to autonomously learn and experiment with various strategies, jointly optimising their cumulative performance. This eventuality could potentially lead to cartel-like

'Sustainable and Unchallenged Algorithmic Tacit Collusion' (2020) 17(2) Northwestern Journal of Technology and Intellectual Property 217, 217 <https://scholarlycommons.law.northwestern.edu/njtip/vol17/iss2/2> accessed 17 July 2024; Ezrachi and Stucke (n 397) 1795-1796.

419 *See* footnote n. 21.

420 *See, e.g.*, OECD (n 403) 14 and footnote n. 417. This area of investigation is the focus of Chapter 4.4.

421 Ibid.

outcomes, where AI trading agents collaborate to achieve shared objectives, despite the absence of an explicit "meeting of minds" between rival firms.[422]

The manifestation of this scenario presents fundamental conceptual and normative challenges. From an external perspective, it will be extremely difficult to determine whether the forms of algorithmic coordination, arising from sequential interactions between algorithms, are the result of deliberate human choice, a random or accidental consequence of AI use.[423] While this uncertainty raises several legal and regulatory issues that require our utmost attention, it is also safe to believe that the potential of AI trading to result in such forms of collusive behaviour will largely depend on the specific technical capabilities of these systems as well as other practical and market factors. But, prior to delving into the technical aspects of ML relevant to this context, it is essential to investigate whether global capital markets or specific segments thereof can foster an economic environment conducive to the emergence of algorithmic variants of 'tacit' collusion.

4.3 The Economics of Algorithmic 'Tacit' Collusion

As capital markets become increasingly digital, the potential risks of algorithmic 'tacit' collusion cannot be overlooked. Yet, determining the probability of the phenomenon of algorithmic collusion must deal with a general ignorance of the phenomenon of algorithmic coordination, as well as the absence of consistent evidence, in the field of financial trading. To bridge this gap, we begin by identifying those market factors that, as stipulated by economic theory, can typically facilitate coordination among competing firms in the absence of direct communication.[424] These factors include (A)

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[422] *Cf.* Giuseppe Colangelo, 'Artificial Intelligence and Anticompetitive Collusion: From the 'Meeting of Minds' towards the 'Meeting of Algorithms' in Martin Ebers, Cristina Poncibò, and Mimi Zou (eds), *Contracting and Contract Law in the Age of Artificial Intelligence* (Hart Publishing) 249-266 <https://ssrn.com/abstract=3751255> accessed 17 July 2024.

[423] *See, e.g.*, OECD (n 21) 33-34.

[424] *But see* Ulrich Schwalbe, 'Algorithms, Machine Learning, and Collusion' (2019) 14 Journal of Computational Law & Economics 568, 592-596 <https://doi.org/10.1093/joclec/nhz004> accessed 17

'market transparency', (B) 'frequency of interactions', (C) 'product homogeneity', (D) 'market concentration', (E) 'entry barriers and innovation', and (F) 'their combined effects'. After substantiating the individual contribution of these factors to the creation of a market environment conducive to algorithmic collusion, we apply them to the context of capital markets in order to evaluate the likelihood of algorithm-enabled 'tacit' collusion.

A. Market transparency

'*Market transparency*' serves as an essential prerequisite for competing firms to effectively monitor prices and understand market dynamics. As a prerequisite to gaining access to market conditions, transparency enables collusive parties to detect any deviation from supra-competitive pricing. This, in turn, facilitates swift retaliation against cheaters and increases the possibility of sustaining collusive outcomes.[425] The financial services industry is well known for its heavy regulation, which includes specific provisions aimed at promoting market transparency. This set of rules is designed to protect various economic and public interests, such as, one among all ensuring the informativeness of market prices. This is in fact considered an essential element in safeguarding investor protection.[426]

July 2024, who affirms that the field of Experimental Economics has shown the vital need for communication for algorithmic collusion. However, the author also notes that most innovative ML-based applications, based on DL methods, can help relax many practical constraints generally faced by competing firms' algorithms to achieve coordination.

425 *See* Marc Vivaldi and others, 'The Economics of Tacit Collusion' (2003) Final Report for DG Competition, European Commission, 22 <https://ec.europa.eu/competition/mergers/studies_reports/the_economics_of_tacit_collusion_en.pdf> accessed 17 July 2024.

426 There is indeed general agreement among academic scholars about the benefits that high levels of market transparency bring to market quality. *See, e.g.*, Mark Lang, Karl V Lins, and Mark Maffett, 'Transparency, Liquidity, and Valuation: International Evidence on When Transparency Matters Most' (2012) 50(3) Journal of Accounting Research 729 <https://doi.org/10.1111/j.1475-679X.2012.00442.x> accessed 17 July 2024, who show that greater transparency at the firm-level has a positive impact on market liquidity and reduces transaction costs; Olena W Watanabe, Michael J Imhof, and Semih Tartaroglu, 'Transparency Regulation and Stock Price Informativeness: Evidence from the European Union's Transparency Directive' (2019) 18(2) Journal of International Accounting Research 89 <https://doi.org/10.2308/jiar-52383> accessed 17 July 2024, who provide evidence of

However, while market transparency primarily aims to safeguard competitive mechanisms and ensure market integrity, it also plays a crucial role in enabling the successful implementation of ML-powered trading. In particular, as discussed in Chapter 2, the safe and reliable performance of ML applications is highly dependent on the availability of large amounts of high-quality data—an aspect that is certainly closely related to the quality of market transparency.

B. Frequency of interactions

The '*frequency of interactions*' also plays a crucial role in facilitating swift responses against cartel cheaters and contributing to the sustainability of collusion. In algorithm-driven markets, a higher frequency of interactions enables more efficient price adjustments, both in terms of speed and cost, thus rendering collusion more sustainable.[427] Capital markets stand out as the fastest and most interconnected markets in the global economy, where market participants interact through trading activity at the speed of light. This is particularly true for highly liquid financial assets and markets that enable HFT—activities that have emerged largely due to the heavy investment and political commitments of the industry players themselves.[428]

the positive impact on price informativeness following the introduction of the Transparency Directive in the EU. At the same time, however, some authors believe that there may be upper limits to the positive contribution of market transparency. *Cf.* Amitai Etzioni, 'Is Transparency the Best Disinfectant?' (2010) 18(4) The Journal of Political Philosophy 389 <https://doi.org/10.1111/j.1467-9760.2010.00366.x> accessed 17 July 2024.

[427] *See* Ivaldi and others (n 425) 19-21.

[428] *See, e.g.*, Donald MacKenzie and others, 'Drilling through the Allegheny Mountains: Liquidity, Materiality and High-Frequency Trading' (2011) 5(3) Journal of Cultural Economy 279 <https://doi.org/10.1080/17530350.2012.674963> accessed 17 July 2024.

C. Product homogeneity

'*Product homogeneity*' is another decisive factor in facilitating collusion, as it reduces the efforts required by participating parties to reach collusive agreements.[429] From the viewpoint of financial investors, the comparison of financial assets primarily revolves around risk-return considerations. Under this lens, financial instruments may be understood as relatively homogeneous products.[430] In addition, the ingenuity of financial engineering also contributes to greater product homogeneity. For instance, with 'synthetic' financial positions, it is in principle possible to replicate the payoff of any financial instrument or portfolio by combining other financial assets.[431]

D. Market concentration

'*Market concentration*' is another factor typically positively associated with the potential for sustaining collusive arrangements more easily. As a general rule, the more competitive a specific industry or market segment is, the fewer economic incentives rival firms have to coordinate their strategies.[432] While certain segments of the financial market, such as equity trading, tend to exhibit higher levels of competition than others,[433] there is still a discernible overall trend towards increasing levels of market

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[429] *See* Ivaldi and others (n 425) 45-47, who argue that collusive behaviour is more difficult to achieve when firms differentiate themselves by different levels of quality in the products they offer. Conversely, product differentiation can have an ambiguous effect on the sustainability of collusion.

[430] In Finance, financial asset or portfolio replication is the activity aimed at replicating the pay-off function of a given target asset or portfolio (i.e. benchmark) under all possible future scenarios. *Cf.* Ron Dembo and Dan Rosen, 'The Practice of Portfolio Replication. A Practical Overview of Forward and Inverse Problems' (1999) 85 Annals of Operations Research 267 <https://doi.org/10.1023/A:1018977929028> accessed 17 July 2024.

[431] A 'synthetic' financial instrument aims to replicate the characteristics (e.g., payoff) of a target financial instrument by combining two or more conventional financial instruments. *See, e.g.*, Mark Rubinstein and Hayne E Leland, 'Replicating Options with Positions in Stock and Cash' (1981) 37(4) Financial Analysts Journal 63 <https://doi.org/10.2469/faj.v37.n4.63> accessed 17 July 2024.

[432] *See* Ivaldi and others (n 425) 12-15, who however note that the presence of asymmetric market shares between rival firms may render collusion more difficult to sustain.

[433] *See* Nicola Cetorelli and others, 'Trends in Financial Market Concentration and Their Implications for Market Stability' (March 2007) Federal Reserve Bank of New York Economic Policy Review 37-41 <https://www.newyorkfed.org/medialibrary/media/research/epr/07v13n1/0703hirt.pdf> accessed

concentration and network interconnections across different markets. This is especially true among major institutional players in the global market.[434]

E. Entry barriers and innovation

Both '*entry barriers*' and '*innovation*' can impact the stability of market concentration levels, albeit in opposite directions. On one hand, high entry barriers are typically considered a significant determinant of the sustainability of collusion. On the other, in innovation-driven markets, concerns regarding collusion are relatively diminished.[435]

Despite financial laws generally aiming to foster a highly competitive landscape and maintaining technological neutrality, the actual reality of global capital markets presents a different picture. For instance, the existence of entry barriers—such as, for instance, licensing requirements, the need for substantial financial, reputational, and human capital, as well as regulatory compliance—creates an environment where the financial sector represents a quite exclusive 'club'.[436] Moreover, while innovation generally enhances market competitiveness, incumbent companies closely monitor

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17 July 2024, who report a general trend of increasing market concentration in US markets, albeit with varying intensity levels among the various market segments.

434 *Cf.* Stefania Vitali, James B Glattfelder, and Stefano Battiston, 'The Network of Global Corporate Control' (2021) 6(10) PloS ONE, Article 225995, 4 <https://doi.org/10.1371/journal.pone.0025995> accessed 17 July 2024, providing evidence of an "economic superentity", formed by major global financial institutions and their international network of company ownerships.

435 Ivaldi and others (n 425) 16-18 and 32-35.

436 In economic terms, certain market segments within the financial services sector exhibit a tendency towards forming 'natural oligopolies', market structures in which a few large firms dominate the industry due to specific characteristics of the market. These characteristics often include high entry barriers, the importance of proprietary technologies, and limited access to essential resources. *See, e.g.*, Paolo Coccorese and Alfonso Pellecchia, 'Deregulation, Entry, and Competition in Local Banking Markets' (2022) 61 Review of Industrial Organization 171 <https://doi.org/10.1007/s11151-022-09867-w> accessed 17 July 2024, who however analyse the evolution of entry barriers in the Italian local banking markets. In addition, also the reputational capital or trust of incumbent companies can be a barrier to market entry for innovative start-ups. *See, e.g.*, Keer Yang, 'Trust as an Entry Barrier: Evidence from FinTech Adoption' (2021) SSRN preprint 1 <https://ssrn.com/abstract=3761468> accessed 17 July 2024.

technological advancements within the industry to remain competitive.[437] Among the various strategies available to limit the threats posed by new entrants, incumbents can always choose, as a last resort, to acquire young innovative companies or their technology solutions to maintain a dominant position.[438]

F. The combined effects of market factors conducive to collusion

According to economic theory, the presence and specific combination of the above market factors can serve as determinants for 'tacit' collusion in a repeated pricing game under oligopolistic settings. However, in markets that are dominated by algorithms, the constraints to achieve coordination without direct communication may be further relaxed.[439] In other words, the use of algorithms can play a decisive role in enabling strategic coordination between rivals. Indeed, algorithmic coordination have an advantage over traditional human-managed cartels due to enhanced analytical capabilities and high speed of action of algorithms.[440]

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[437] For an in-depth examination of the effects of technological innovation on the financial services industry as well as related regulatory implications, see Teresa Rodriguez de las Heras Ballell, 'The Layers of Digital Financial Innovation: Charting a Regulatory Response' (2020) 25 Fordham Journal of Corporate & Financial Law 381 <https://ir.lawnet.fordham.edu/jcfl/vol25/iss2/2> accessed 17 July 2024; *see also* Erik Feyen and others, 'Fintech and the digital transformation of financial services: implications for market structure and public policy' (2021) BIS Papers No 117, July 2021 <https://www.bis.org/publ/bppdf/bispap117.pdf> accessed 17 July 2024, who discuss the implications to competition in the financial sector associated with FinTech.

[438] *See, e.g.*, Divya Anand and Murali Mantrala, 'Responding to disruptive business model innovations: the case of traditional banks facing fintech entrants' (2019) 3 Journal of Banking and Financial Technology 19 <https://doi.org/10.1007/s42786-018-00004-4> accessed 17 July 2024; *but see* Dirk A Zetzsche and others, 'From FinTech to TechFin: The Regulatory Challenges of Data-Driven Finance' (2018) 14(2) New York University Journal of Law & Business 393, 402 <https://www.nyujlb.org/_files/ugd/716e9c_2d238eae54ac4d35abb655dddb91f256.pdf> accessed 17 July 2024, who argue that incumbent financial firms have gradually faced greater competitive challenges due to the increasing number and variety of new entrants in the sector.

[439] *See* OECD (n 403) 24-32, describing four scenarios in which the use of algorithms by competing firms may lead to tacit collusion, including: (i) 'monitoring algorithms', (ii) 'parallel algorithms', (iii) 'signalling algorithms', and (iv) 'self-learning algorithms'.

[440] *E.g.*, Gal (n 397) 78-79.

As the field of ML continues to advance, self-learning algorithms could lead to new forms of cartel-like behaviours. In particular, if competing trading algorithms become 'transparent' to each other, they might be able to coordinate behaviour by predicting rivals' strategies without the need for direct communication. By altering the nature of the 'communication' required to reach an illicit agreement, algorithmic agents could thus give rise to tacit collusion.[441]

In light of the foregoing, specific market segments within the complex network of global capital markets, which possess some of the aforementioned factors, may become more susceptible to algorithmic coordination, bringing forth new and unprecedented risks of tacit collusion. Nonetheless, it remains uncertain *whether* and effectively *how* independent AI trading agents can coordinate their behaviour without being expressively programmed or instructed to do so. Moreover, given the complexity inherent in capital markets trading, some sort of communication between rival algorithms might still be necessary for establishing and sustaining coordination.[442] In order to shed light on these matters, in the next sub-section we will explore the feasibility of algorithmic tacit collusion in real-world markets through an analysis of state-of-the-art theoretical and experimental research conducted in the field of Computational Economics. As we shall see, the most spectacular findings regard the same ML paradigm on which our investigation is centred: artificial agents based on RL methods.

4.4 Reinforcement Learning Agents and Algorithmic Collusion

Recent years has seen a surge of scientific interest in the understanding of the economics of algorithmic behaviour and coordination in market contexts. Specifically,

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[441] *E.g.*, ibid 85.

[442] *See, e.g.*, footnote n. 424; *but see* Martino Banchio and Giacomo Mantegazza, 'Artificial Intelligence and Spontaneous Collusion' (2023) arXiv preprint 1 <https://arxiv.org/pdf/2202.05946.pdf> accessed 17 July 2024, who support the idea that the tendency of algorithms to coordinate behaviour is inherent in the way they interact in markets, calling this phenomenon "spontaneous coupling".

economic researchers use game theory and computational approaches to explore the potential for algorithmic cooperative behaviour in oligopolistic market settings.[443] In what follows, we provide an overview of some of the most relevant and significant research conducted in Computational Economics. However, acknowledging the innovative character and extremely fast-paced development of this fascinating scientific field, it will not be possible to give an exhaustive account.

A. Findings from Computational Economics studies

From both (*i*) theoretical, (*ii*) empirical, and (*iii*) experimental perspectives, recent research in the field of Computational Economics shows that the scenario of tacit collusion by autonomous algorithmic agents may be more than just a sci-fi fantasy.

i. Theoretical research

Despite its quite simplistic assumptions, a recent theoretical study by *Salcedo (2015)* has indeed attracted significant scholarly attention due to its remarkable findings. In a duopoly with homogeneous products, even relatively basic pricing algorithms—i.e. hence non-ML—tend to achieve collusive results. Specifically, when competing algorithms are able decode rivals' strategies and, on the basis of this knowledge, can

443 A good number of experts in the field are somewhat sceptical about the validity of the results obtained from the emerging research in Computational Economics. *See, e.g.*, Ashwin Ittoo and Nicolas Petit, 'Algorithmic Pricing Agents and Tacit Collusion: A Technological Perspective' in Hervé Jacquemin and Alexandre De Streel (eds), *L'Intelligence Artificielle et le Droit* (Larcier 2017) 241-256 <https://ssrn.com/abstract=3046405> accessed 17 July 2024; Schwalbe (n 424); Kai-Uwe Kühn and Steven Tadelis, 'The Economics of Algorithmic Pricing: Is Collusion Really Inevitable? (2018) Unpublished Manuscript <http://faculty.haas.berkeley.edu/stadelis/Algo_Pricing.pdf> accessed 17 July 2024; Thibault Schrepel, 'The Fundamental Unimportance of Algorithmic Collusion for Antitrust Law' (*JOLT Digest*, 2020) <http://jolt.law.harvard.edu/digest/the-fundamental-unimportance-of-algorithmic-collusion-for-antitrust-law> accessed 17 July 2024; Florian E Dorner, 'Algorithmic Collusion: A Critical Review' (2021) arXiv preprint 1 <https://doi.org/10.48550/arXiv.2110.04740> accessed 17 July 2024; Arnoud V den Boer and others, 'Artificial Collusion: Examining Supracompetitive Pricing by Q-learning Algorithms' (2022) Tinbergen Institute Discussion Paper, No. TI 2022-067/VII 1, 36 <http://hdl.handle.net/10419/265843> accessed 17 July 2024; Steven Van Uytsel, 'The Algorithmic Collusion Debate: A Focus on (Autonomous) Tacit Collusion' in Steven Van Uytsel, Salil Mehra, and Yoshiteru Uemura (eds), *Algorithms, Collusion and Competition Law* (Edward Elgar Publishing 2023) 1-38 <https://doi.org/10.4337/9781802203042.00009> accessed 17 July 2024.

revise and align own strategy in response, collusion becomes an inevitable outcome.[444] Although capturing the idea of tacit collusion in a mathematically elegant way,[445] the underlying model assumptions of this research, particularly algorithms' ability to communicate to coordinate, have been criticised as highly unrealistic.[446]

Motivated by advances in ML methods, a more recent research paper by *Cartea and others (2022)* provides further theoretical support for the notion that autonomous artificial agents are capable of learning collusive behaviours as an optimal strategy. In particular, it shows that self-interested algorithmic agents can learn, through repeated interactions, to initiate a collusive arrangement on prices and sustain it without the need for direct communication.[447] Although, in light of these findings, there are no major theoretical limits to the feasibility of tacit collusion, this does not necessarily imply that algorithmic collusion is a concrete risk in real-life market contexts characterised by high complexity.

ii. Empirical research

Nevertheless, empirical research seems to confirm that certain markets may be subject to collusion due to the presence of pricing algorithms. For instance, using pricing data from the German retail gasoline industry, *Assad and others (2023)* found some evidence of the negative effects on competition caused by the widespread adoption of pricing algorithms among rival firms. Their findings suggest that in algorithm-dominated markets, competing pricing algorithms may facilitate the occurrence of tacit collusion,

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444 *See* Bruno Salcedo, 'Pricing Algorithms and Tacit Collusion' (2015) Unpublished Manuscript <https://brunosalcedo.com/docs/collusion.pdf> accessed 17 July 2024, who provides theoretical evidence of tacit collusion between two competing pricing algorithms.

445 Rohit Lamba and Sergey Zhuk, 'Pricing with Algorithms' (2022) arXiv preprint 1, 3 <https://arxiv.org/pdf/2205.04661.pdf> accessed 17 July 2024.

446 *E.g.*, ibid 27-28; Schwalbe (n 424) 591-592.

447 *See* Álvaro Cartea and others, 'Learning to Collude: A Folk Theorem for Algorithms' (2022) SSRN preprint 1 <https://ssrn.com/abstract=4293831> accessed 17 July 2024.

leading to higher prices for retail consumers.[448] Another recent research paper, focusing on the *Amazon* platform's marketplace, obtained similar evidence.[449] If theoretical and empirical research opens the door to the possibility of tacit collusion by algorithms, it is perhaps findings from the field of experimental research in Computational Economics that most draw our attention to the phenomenon.

iii. Experimental research

Scholars in the field of Experimental Economics have long supported the hypothesis that, at least in the context of a duopoly, independent RL-based agents may exhibit collusive-like behaviour in sequential games.[450] Indeed, only in the last few years, a wave of published work has provided growing evidence about algorithmic tacit collusion even in more complex market environments. Importantly, most of these research studies employ RL—which, as discussed in Chapter 2.4, is the foundational paradigm for artificial trading agents—to analyse the phenomenon of algorithmic coordination in oligopolistic markets.[451] More specifically, the current focus is on a specific sub-category of RL methods knowns as 'Q-learning'[452] algorithms. These

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448 *See* Stephanie Assad and others, 'Algorithmic Pricing and Competition: Empirical Evidence from the German Retail Gasoline Market' (2023) Journal of Political Economy (forthcoming) <https://doi.org/10.1086/726906> accessed 17 July 2024; *but see* Kühn and Tadelis (n 443).

449 *See* Leon Musolff, 'Algorithmic Pricing Facilitates Tacit Collusion: Evidence from E-Commerce' in *EC '22: Proceedings of the 23rd ACM Conference on Economics and Computation* (ACM 2022) 32-33 <https://dl.acm.org/doi/10.1145/3490486.3538239> accessed 17 July 2024.

450 *See* Gerald Tesauro and Jeffrey O Kephart, 'Pricing in Agent Economies Using Multi-Agent Q-Learning' (2002) in Simon Parsons, Piotr Gmytrasiewicz, and Michael Wooldridge (eds), *Game Theory and Decision Theory in Agent-Based Systems* (Springer Science+Business Media 2022) 293-313 <https://doi.org/10.1007/978-1-4615-1107-6_14> accessed 17 July 2024, assuming however that competing firms' pricing algorithms need to enjoy, by default, the ability to decode rivals' strategies in order to achieve some form of coordination.

451 For a concise overview of recent research employing Q-learning methods, see Axel Gautier, Ashwin Ittoo, and Pieter Van Cleynenbreugel, 'AI Algorithms, Price Discrimination and Collusion: A Technological, Economic and Legal Perspective' (2020) 50 European Journal of Law and Economics 405, 418-420 <https://doi.org/10.1007/s10657-020-09662-6> accessed 17 July 2024.

452 'Q-learning' is a model-free, value-based, and off-policy reinforcement learning algorithm (i.e. 'critic-only' approach) and it represents one of the most researched RL methods to solve optimisation problems in finance. *See, e.g.*, Fischer (n 194) 4-19, who provides a comprehensive introduction to

algorithms follow an adaptive approach that enables them to dynamically learn the strategic environment through their own actions over time.[453] While financial institutions may not currently employ this specific class of RL algorithms for executing trading orders or setting market prices,[454] these algorithms already find widespread use in various other application domains.[455] Thus, potential adoption of Q-learning (and similar RL methods) in the financial sector in the foreseeable future remains plausible. This speculation is bolstered by the trajectory observed in state-of-the-art research in Deep Computational Finance, as examined in Chapter 2.4 above.

Against this backdrop, in-lab experimental studies show that, under somewhat controlled environments, competing RL-based pricing agents achieve supra-competitive equilibria, entailing risks of algorithmic collusion. According to *Klein (2021)*, in a duopoly where rival firms independently employ Q-learning pricing agents in a sequential game, the agents can learn to approximate profitable fixed prices or generate asymmetric price cycles in the face of competitive pressure.[456] As observed in

these RL methods, as well as an exhaustive review on studies employing Q-learning algorithms for solving different financial trading problems.

453 *E.g.*, Stephanie Assad and others, 'Autonomous Algorithmic Collusion: Economic Research and Policy Implications' (2021) 37(3) Oxford Review of Economic Policy 459, 464 <https://doi.org/10.1093/oxrep/grab011> accessed 17 July 2024.

454 AFM (n 105) 3.

455 *See* Beakcheol Jang and others, 'Q-Learning Algorithms: A Comprehensive Classification and Applications' (2019) 7 IEEE Access 133653, 133661-133664 <https://doi.org/10.1109/ACCESS.2019.2941229> accessed 17 July 2024, describing the application of Q-learning algorithms to solve tasks in various domains, such as industrial processes, network process, game theory, robotics, operation research, control theory, and image recognition.

456 *See* Timo Klein, 'Autonomous Algorithmic Collusion: Q-Learning Under Sequential Pricing' (2021) 52(3) The RAND Journal of Economics 538 <https://doi.org/10.1111/1756-2171.12383> accessed 17 July 2024, highlighting that not only the significance of algorithms' properties but also the specific characteristics of the market environment in which these algorithms operate play a crucial role to facilitate collusion.

the literature, these unusual market outcomes are typically observable in those contexts where tacit collusion is likely to occur.[457]

According to extremely influential research by *Calvano and others (2020)*, independent Q-learning pricing algorithms, in an oligopoly model of infinitely repeated price competition where they can observe rivals' price, show the tendency to learn, through trial-and-error mechanism, how to collude even without prior knowledge about their operating environment.[458] Algorithms engage in reward-punishment schemes to strategically cooperate to fix price above competitive levels. The authors, however, note that learning these strategies can be time-consuming and require a great deal of experimentation, rendering collusion a costly activity.[459] Despite some research limitation, however, this research paper offers important insights into profit-driven systematic collusion beyond the duopoly context.[460]

In subsequent research, *Calvano and others (2021)* further validate the potential occurrence of algorithmic tacit collusion, even under the constraints of imperfect monitoring. Without direct access to rivals' pricing strategies and being limited to observing only aggregate market prices, identical Q-learning algorithms, when left to interact over extended timeframes, demonstrate the ability to learn sophisticated

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457 Eric Maskin and Jean Tirole, 'A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles' (1988) 56 Econometrica 571, 592 <https://doi.org/10.2307/1911701> accessed 17 July 2024.

458 *See* Emilio Calvano and others, 'Artificial Intelligence, Algorithmic Pricing, and Collusion' (2020) 110(10) American Economic Review 3267, 3294-3296 <https://doi.org/10.1257/aer.20190623> accessed 17 July 2024.

459 Ibid, stating, however, that further research is needed to confirm the robustness of these early results, as the external validity of most laboratory experiments is challenged by the actual settings of markets which can often be highly complex.

460 *See, e.g.*, Gautier, Ittoo, and Van Cleynenbreugel (n 451) 427-428.

reward-punishment mechanisms enabling collusive outcomes without explicit communication.[461]

In light of the impressive experimental findings, it is foreseeable that this field will attract growing interest from researchers in the coming years. While emerging research is somewhat limited in methodologies, rendering its results not entirely generalisable to real and significantly more complex market environments, future research will need to shed further light on the specific mechanics underpinning algorithmic tacit collusion.

Given the multiplicity of strategies available to algorithmic agents and the possible market structures in which they operate, it is indeed necessary to better understand those factors that facilitate algorithms to learn how to coordinate their strategies. A first attempt in this direction is certainly the work of *Cartea and others (2022)*, which introduces the concept of the 'algorithmic learning equations' to study the evolution of algorithmic strategies, their interaction, and resulting effects to competition.[462]

Overall, while the emerging branch of scientific research on algorithmic collusion is still at its early stage, its findings undoubtedly contribute to expanding our knowledge of RL agents and their potential to result in algorithmic collusion in various oligopolistic settings. Despite some initial evidence, the ability of RL agents to coordinate behaviour in complex environment may face several challenges. State-of-the-art research in this field still not provide conclusive evidence but rather leave us with a number of open questions, as discussed below.

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461 *See* Emilio Calvano and others, 'Algorithmic Collusion with Imperfect Monitoring' (2021) 79 International Journal of Industrial Organization, Article 102712 <https://doi.org/10.1016/j.ijindorg.2021.102712> accessed 17 July 2024.

462 *See* Álvaro Cartea and others, 'The Algorithmic Learning Equations: Evolving Strategies in Dynamic Games' (2022) SSRN preprint 1 <https://ssrn.com/abstract=4175239> accessed 17 July 2024.

B. Challenges and open questions

A review of the literature reveals three main categories of technical and practical challenges that may ultimately render algorithmic collusion less likely to occur. Namely, these challenges relate to: (i) the degree of algorithm sophistication that would be necessary to enable strategic coordination, (ii) the complexity of the operational environment, which can severely limit the ability of rival algorithms to coordinate, and (iii) the level of communication eventually required for coordination to be established and sustained over time.

i. Level of algorithm sophistication

It is unclear what level of sophistication algorithms ought to enjoy in coordinating strategies with their rivals. In fact, modestly sophisticated RL-based methods—such as the abovementioned Q-learning algorithms—may encounter various limitations, of both technical and practical nature, in learning suitable strategies for establishing coordination in highly complex and competitive environments.[463] It seems reasonable to think that, especially in very dynamic and complex market environments, only more sophisticated algorithms (e.g., based on DL) would be capable of observing, analysing, deciphering and then coordinating the market strategy of rivals without the need for direct communication. Some researchers believe that DRL methods (e.g., deep Q-learning)—which allow to establish increasingly powerful and autonomous artificial agents through the combination of RL and DL—could relax some of these challenges faced by algorithms to tacitly collude.[464]

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[463] *E.g.*, Ittoo and Petit (n 443) 256; Schwalbe (n 424) 599-600.

[464] *See, e.g.*, Matthias Hettich, 'Algorithmic Collusion: Insights from Deep Learning' (2021) CQE Working Papers 9421, Center for Quantitative Economics (CQE), University of Münster <https://www.wiwi.uni-muenster.de/cqe/sites/cqe/files/CQE_Paper/cqe_wp_94_2021.pdf> accessed 17 July 2024, showing that deep Q-learning agents can achieve collusive outcomes faster than other methods. The author also points out the likelihood of algorithmic collusion diminishes with an increasing number of rival algorithms. However, the existence of rule-based algorithms or human price-setter with infrequent pricing does not necessarily complicate collusion.

By contrast, other researchers are of the opinion that collusion may exclusively arise when rather simple algorithms are involved.[465] This idea aligns with the seminal work of Robert Axelrod—an American political scientist renewed for his pioneering research on understanding cooperation in competitive environments using Game Theory—suggesting that strategies should not be too complex to enable cooperative strategies to emerge and be sustained over time.[466] It should also be noted that while certain algorithms are sophisticated, their strategies, as observed by other agents, may not necessarily be complex to decipher.[467] For some other researchers, instead, collusive outcomes do not require high algorithmic sophistication, but rather may emerge from algorithms whose exploration of space and action policies in the learning phase is incomplete.[468] According to this view, regulation should therefore target RL-based agents' learning phases, including the relevant design choices (e.g., hyperparameters, reward function, etc.).[469]

On a slightly different note, according to recent research, algorithmic collusive behaviour may arise both as a consequence of AI 'intelligence' and AI 'stupidity'.[470] In particular, researchers have unveiled two distinct mechanisms that may be conducive to the emergence of collusion. On the one hand, the growing capabilities of AI trading

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465 For a concise review of the scientific debate on this issue, see Hans-Theo Normann and Martin Sternberg, 'Do Machines Collude Better than Humans?' (2021) 12(10) Journal of European Competition Law & Practice 765, 767-768 <https://doi.org/10.1093/jeclap/lpab082> accessed 17 July 2024; *see also* Ai Deng, 'When Machines Learn to Collude: Lessons from a Recent Research Study on Artificial Intelligence' (2017) SSRN preprint 1 <https://ssrn.com/abstract=3029662> accessed 17 July 2024.

466 *See* Robert Axelrod, *The Evolution of Cooperation* (Basic Books 1984) 120-123.

467 *E.g.*, Normann and Sternberg (n 467) 768.

468 Ibrahim Abada and Xavier Lambin, 'Artificial Intelligence: Can Seemingly Collusive Outcomes Be Avoided?' (2023) 69(9) Management Science 4973 <https://doi.org/10.1287/mnsc.2022.4623> accessed 17 July 2024.

469 *Cf.* footnotes n. 189-192 and accompanying text.

470 Winston W Dou, Itay Goldstein, and Yan Ji, 'AI-Powered Trading, Algorithmic Collusion, and Price Efficiency' (2023) SSRN preprint 1 <https://ssrn.com/abstract=4452704> accessed 17 July 2024.

systems might enable competing algorithms to discover price-triggering strategies, allowing them to achieve supra-competitive outcomes.[471] On the other hand, due to biases in the learning process coupled with algorithmic homogenisation, some collusive outcomes may arise in ways akin to so-called 'hub-and-spoke'[472] forms of collusion.[473]

Overall, the relationship between algorithmic sophistication and collusion remains ambiguous. While the likelihood and magnitude of the risk of tacit collusion by autonomous agents remain to be fully understood, effective implementation of collusive algorithms may ultimately require three main components: (*i*) a 'collusive' one, (*ii*) a 'competitive' one, and (*iii*) a 'switching mechanism'.[474] Hence, while competing algorithms may inadvertently coordinate behaviour, at least for a short period of time, it still seems reasonable to think that they must be explicitly programmed and trained by human experts to successfully achieve some concrete collusive outcome, especially in complex environments. In such a case, though, it would be no longer appropriate to speak of algorithmic 'tacit' collusion, as humans merely use algorithms to accomplish non-competitive market behaviours.[475]

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471 Ibid 34-44.

472 On the relationship between 'hub-and-spoke' frameworks and algorithmic 'tacit' collusion, see Ariel Ezrachi and Maurice E Stucke, 'The Role of Secondary Algorithmic Tacit Collusion in Achieving Market Alignment' (2023) Working paper CCLP(L)54, 8-18 <https://ssrn.com/abstract=4546889> accessed 17 July 2024.

473 Dou, Goldstein, and Ji (n 470) 44-50.

474 *E.g.*, den Boer and others (n 443) 36.

475 *E.g.*, ibid 37-38.

ii. *The complexity of market environments*

The complexity of the environment in which competing algorithmic agents are called to operate also requires further investigation to understand the likelihood of tacit collusion. Several aspects play a crucial role in this context:

(i) the number of competing agents;

(ii) the variety of the types of agents, both human and algorithmic, involved; and

(iii) the specific rules governing the operation of the markets in question.

First, the number of competing algorithmic agents could be a key determinant. Generally, as the number of participants increases, the risks of collusion quickly vanish.[476] This principle is also observed by the experimental studies previously discussed, which indeed show more robust findings in duopoly settings.[477]

Second, the variety of agents involved can influence the likelihood of collusion. When competing algorithms share similar strategies, their ability to understand and coordinate with each other increases.[478] Situations where competing firms deploy pricing algorithms acquired from the same third-party providers may further facilitate this scenario.[479] Additionally, when algorithms sophisticated enough to be able to coordinate face competition from rule-based algorithms, their ability to coordinate seems to remain unchanged.[480] On the other hand, the presence of human competitors

[476] *See, e.g.*, Calvano and others (n 458); Hettich (n 464) 13-16.

[477] *See* footnotes n. 456 and 458.

[478] *E.g.*, Calvano and others (n 458); Hettich (n 464) 16.

[479] Hettich (n 464) 16.

[480] *See* ibid 14-15.

in heterogeneous markets may limit tacit collusion. When competing with humans, algorithms seem to lose their anti-competitive attitude substantially.[481] Only when algorithmic agents significantly out-number human competitors do the risks of collusion become more relevant.[482] However, if human competitors become aware of the presence of rival algorithms and are able to learn their strategies, the likelihood of collusion may be impaired as the former may have incentives to exploit the latter to their advantage.[483]

Third, the specific rules governing market functioning play a significant role. The types of action available as well as underlying mechanisms on the basis of which algorithms operate and interact, which are heavily influenced by market characteristics, may constrain algorithmic forms of coordination.[484] Most research on algorithmic collusion, however, tends to disregard some of the fundamental features of real-world marketplaces and the uncertainty that characterises them.[485] As such, their findings might not be readily generalisable in the context of complex environments such as capital markets.

iii. The role of communication

One last key aspect to consider in our analysis concerns the role of communication necessary for competitive algorithms to achieve strategic coordination. While existing

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481 *See, e.g.*, Micah Carrol and others, 'On the Utility of Learning about Humans for Human-AI Coordination' in *NIPS '19: Proceedings of the 33rd International Conference on Neural Information Processing Systems (NeurIPS 2019)* (ACM 2019), Article 465 <https://dl.acm.org/doi/10.5555/3454287.3454752> accessed 17 July 2024.

482 *See, e.g.*, Hans-Theo Normann and Martin Stenberg, 'Human-Algorithm Interaction: algorithmic Pricing in Hybrid Laboratory Markets' (2023) 152 European Economic Review, Article 104347 <https://doi.org/10.1016/j.euroecorev.2022.104347> accessed 17 July 2024.

483 *See* Tobias Werner, 'Algorithmic and Human Collusion' (2022) SSRN preprint 1, 30-33 <https://ssrn.com/abstract=3960738> accessed 17 July 2024.

484 *E.g.*, Assad and others (n 453) 477.

485 *E.g.*, Steven Van Uytsel (n 443) 17-18.

experimental research suggests that algorithms may be able to learn how to coordinate without the need for direct communication, it is, unfortunately, unable to provide conclusive evidence.[486]

However, two noteworthy observations warrant attention here. First, the validity of abovementioned scientific research can be undermined by overly simplistic assumptions, including that algorithmic strategies are transparent among rivals. In particular, the fact that specific trading agents may act as black boxes may *a fortiori* prevent the possibility of coordination between rival firms.[487] Second, while it is true that laboratory experiments exploring RL methods provide valuable insights, their findings still need to be more generalisable to real-world markets. Independent AI trading systems may face several challenges in coordinating strategies to attain supra-competitive price levels just by monitoring market prices and co-adapting to observed market conditions. As such, most existing research risks underestimating all the complexity involved in solving coordination problems with ML methods. While some form of communication between algorithms may still be indispensable for collusion to arise in real-life settings,[488] critics of the algorithmic tacit collusion conjecture believe that algorithms are unable to communicate and exchange strategic information in real-life applications.[489]

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486 *See* Schwalbe (n 424) 594, stating that "*the question arises whether algorithms can communicate with each other or whether different algorithms might even be able to learn to communicate without being explicitly programmed, that is, without a common communication protocol.*"

487 *E.g.*, ibid 589.

488 For an overview of possible mechanisms allowing algorithmic agents to solve communication problems in order to coordinate behaviour, see Wei Du and Shifei Ding, 'A Survey on Multi-Agent Deep Reinforcement Learning: From the Perspectives of Challenges and Applications' (54) Artificial Intelligence Review 3215, 3225-3227 <https://doi.org/10.1007/s10462-020-09938-y> accessed 17 July 2024.

489 *See, e.g.*, Ittoo and Petit (n 443) 253-256, who identify five main challenges faced by RL-based agents that would defuse the algorithmic tacit collusion conjecture. Namely, (i) preference specification; (ii) formalisation of the environment and the data problem; (iii) non-stationary agents and preference construction; (iv) scalability; and (v) exploration versus exploitation trade-off; *see also* Schwalbe (n 424) 594.

In principle, the ability for algorithms to communicate with each other may either result from pre-programming by human experts or be autonomously developed by the same algorithms.[490] In the former case, however, we would no longer be able to speak of tacit collusion as humans would be required to agree on a given communication protocol *a priori*. The feasibility of the latter case, instead, would strictly depend on the ability of competing algorithms to learn how to exchange information for purposes not pre-defined by human experts with a potentially large number of other agents, possibly based on different methods.[491] However, existing research does not shed light on this aspect. Hence, the distinction between whether algorithms can develop communication skills or just the ability to effectively co-adapt with rivals in the learning environment remains to be determined.[492]

In addition to scenarios of algorithmic collusion involving reciprocal communication, there exist another possible cause for collusion-like outcomes to occur, which however only involve unilateral communication. This is the so-called scenario of 'adversarial collusion'. In this scenario, collusion may arise as a result of an attacker manipulating one or more target algorithms, leading to supra-competitive market conditions that may benefit all involved firms.[493] While adversarial collusion poses adverse effects on competition, it differs from scenarios in which autonomous AI agents engage in tacit collusion. Indeed, it is reasonable to believe that this form of

490 *E.g.*, Dorner (n 443) 1.

491 *See* Normann and Sternberg (n 467) 769-770.

492 *See* Angeliki Lazaridou and Marco Baroni, 'Emergent Multi-Agent Communication in the Deep Learning' (2020) arXiv preprint 1, 17 <https://doi.org/10.48550/arXiv.2006.02419> accessed 17 July 2024; *see also* Emilio Calvano and others, 'Algorithmic Collusion: Genuine or Spurious?' (2023) 90 International Journal of Industrial Organization, Article 102973 <https://doi.org/10.1016/j.ijindorg.2023.102973> accessed 17 July 2024, referring to collusive-like effects on markets due to algorithmic co-adaption as 'spurious collusion'.

493 *See, e.g.*, Luc Rocher, Arnoud J Tournier, and Yves-Alexandre de Montjoye, 'Adversarial Competition and Collusion in Algorithmic Markets' (2023) 5 Nature Machine Intelligence 497 <https://doi.org/10.1038/s42256-023-00646-0> accessed 17 July 2024.

market abuse requires some human direction, making it more fitting to be categorised within the 'AI as victim' concept discussed earlier in this chapter.

Overall, inasmuch as tacit collusion is a coordination problem, the question of algorithmic collusion arising without explicit communication remains open to further empirical investigation.[494] Some researchers nevertheless believe that, thanks to advances in computational methods, algorithms may find ways to collude without human guidance or assistance.[495] Technological progress may arguably enable autonomous algorithmic agents to develop innovative means to achieve strategic coordination that does not require direct communication.[496] Perhaps, ongoing advancements in DRL methods might aid in surmounting current obstacles algorithms face in achieving tacit collusion.

C. Implications for capital markets and preliminary evidence

While Computational Economics research offers initial insights into the risks of algorithmic tacit collusion to emerge in digital markets, it is essential to exercise caution when extrapolating these findings to the complex domain of capital markets. Due to their unique properties, indeed, capital markets present a number of challenges for modelling of RL agents' behaviour and assessing their potential for strategic coordination.

494 *But see* Maximilan Andres, Lisa Bruttel, and Jana Friedrichsen, 'How Communication Make the Difference Between a Cartel and Tacit Collusion: A Machine Learning Approach' (2023) 152 European Economic Review, Article 104331 <https://doi.org/10.1016/j.euroecorev.2022.104331> accessed 17 July 2024, supporting, through experimental research, the argument that collusive outcomes necessitate direct communication among rival firms.

495 *See, e.g.*, Timo Klein, '(Mis)understanding Algorithmic Collusion' (2020) 1(1) Antitrust Chronicle 53 <https://www.competitionpolicyinternational.com/wp-content/uploads/2020/07/AC-July-I.pdf> accessed 17 July 2024.

496 *Cf.* Schwalbe (n 424) 596, arguing that: "*[t]he development of algorithms that can learn to communicate with each other seems to be in its very early stages. Although it remains unclear which types of communication among algorithms might arise in the future, for now different pricing algorithms should not expected to be able to communicate with each other . . . or . . . to decode other algorithms and achieve collusion*".

First, the forces of demand and supply of financial assets, including the speed at which they evolve over time, require different modelling techniques than those suitable for the study of other retail marketplaces. Second, concerns of market power that often arise in other contexts are relatively less pronounced in financial markets.[497] Third, the highly dynamic and complex nature of financial markets, characterised by statistical noise and significant unpredictability, may hinder the ability of rival trading algorithms to become transparent to each other.[498] Despite these challenges, we believe there is a need for further research on risks arising from the market behaviour and interaction between algorithmic agents. Indeed, even the slightest price impact resulting from algorithmic forms of coordination could have substantial negative effects for the quality and integrity of capital markets, posing potential threats to their overall stability.[499]

Hence, the risks of algorithmic collusion in capital markets should not be completely overlooked.[500] Recent scientific endeavours have begun exploring the possible impact of RL agents on competition in this domain. Early experimental studies have addressed the potential for tacit collusion to occur in a number of different market settings. For instance, a research paper by *Cartea, Chang, and Penalva (2022)* reveals that when competing liquidity providers firms (i.e. market makers) employ RL trading algorithms, in a repeated game context, supra-competitive price equilibria can emerge. Despite each algorithm's inability to directly observe rivals' pricing strategies, rival algorithms can learn to tacitly collude even if can only rely on receiving noisy rewards

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497 Calvano and others (n 458) 34.

498 *Cf.* Schwalbe (n 424) 570 and 592.

499 Even the tiniest event of market failure in a particular segment of the capital markets could cascade to undermine the stability of the entire system (i.e. the so-called 'butterfly effect'). *Cf.* Youngna Choi and Raphael Douady, 'Financial Crisis Dynamics: Attempt to Define a Market Instability Indicator' (2012) 12(9) Quantitative Finance 1351, 1351-1352 <https://doi.org/10.1080/14697688.2011.627880> accessed 17 July 2024.

500 *See, e.g.*, Assad and others (n 453) 478.

from their trading activity. In particular, the authors show that algorithms achieve coordination by adapting their trading strategies to changes in their rewards as a result of the actions of rival algorithms. Moreover, they emphasise that the tick size significantly affects the occurrence of collusive behaviours, with smaller tick size encouraging competition and reducing trading costs among all market participants.[501] Recent research also examines the behaviour of AI trading agents in dealer markets, uncovering experimental evidence of algorithms tacitly colluding through non-competitive bid/ask pricing. Notably, several studies establish a link between the number of competing firms and the degree of competition in these markets, indicating that greater number of competing algorithms reduces the risk of pricing coordination.[502]

Notwithstanding some preliminary evidence offered by experimental research, the concrete materialisation of risks of algorithmic tacit collusion in capital markets remains to be definitely ascertained. It should however be acknowledged that, even in the absence of true strategic coordination, the collective actions of independent trading algorithms could lead to unfavourable market conditions for other market participants, including market manipulation.[503] Therefore, in view of the rapid advancements in ML research and practice within financial trading, both regulators and researchers in this domain should delve deeper into the various forms of algorithmic coordination that

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501 *See* Álvaro Cartea, Patrick Chang, and José Penalva, 'Algorithmic Collusion in Electronic Markets: The Impact of Tick Size' (2022) SSRN preprint 1 <https://ssrn.com/abstract=4105954> accessed 17 July 2024.

502 *See* Wei Xiong and Rama Cont, 'Interactions of Market Making Algorithms: A Study on Perceived Collusion' in *ICAIF '21: Proceedings of the Second ACM International Conference on AI in Finance* (ACM 2022), Article 32, 1 <https://doi.org/10.1145/3490354.3494397> accessed 17 July 2024; Álvaro Cartea and others, 'AI-Driven Liquidity Provision in OTC Financial Markets' (2022) 22(12) Quantitative Finance 2171 <https://doi.org/10.1080/14697688.2022.2130087> accessed 17 July 2024; Rama Cont and Wei Xiong, 'Dynamics of Market Making Algorithms in Dealer Markets: Learning and Tacit Collusion' (2023) Mathematical Finance (forthcoming) <https://doi.org/10.1111/mafi.12401> accessed 17 July 2024.

503 *See* OECD (n 135) 27-28, advancing the idea that competing algorithmic trading systems may give rise to collective forms of market manipulation based on spoofing strategies; *see also* Álvaro Cartea and others (n 377).

may occur. Although capital markets trading is generally considered a highly competitive industry, specific market segments therein could be more prone to risks of coordination among rival ML-powered trading systems. With this consideration in mind, the next section examines, from a conceptual standpoint, the validity of these risks through two case studies.

4.5 Case Studies

From a conceptual standpoint, we now explore whether, because their operational mechanisms and institutional structures, certain segments of capital markets may be prone to risks of 'tacit' collusion by autonomous AI trading systems. Without pretending to provide an exhaustive account, we will focus on 'quote-driven' and 'financial benchmark' markets.

A. Quote-driven markets

Quote-driven markets are characterised by a relatively concentrated number of designed professionals known as 'market makers', who compete by continuously publishing 'bid' and 'ask' prices (i.e. 'quotes'), reflecting their willingness to provide liquidity to the markets. Unlike order-driven markets, buy and sell orders do not directly interact in a quote-driven market. Thus, buyers and sellers interact one-to-one with market makers, who profit from the bid-ask price spread, compensating for the risk of holding inventories. In addition, market makers adjust their quotes periodically based on market conditions, inventory status, and competition with other market makers.[504] At first glance, one could say that the way market makers display their quotes somewhat resembles how prices are offered in the retail gasoline station

504 Estelle Cantillon and Pai-Ling Yin, 'Competition between Exchanges: A Research Agenda' (2011) 29(3) International Journal of Industrial Organization 329, 330 <https://doi.org/10.1016/j.ijindorg.2010.12.001> accessed 17 July 2024.

business, an industry that notoriously has suffered from risks of cartel-like behaviour among competing firms.[505]

Nevertheless, let us consider a scenario in which a given number of market makers, all employing AI trading systems, compete in a somewhat oligopolistic market setting, such as bond markets.[506] Furthermore, let us posit a scenario in which these rival firms can also engage in direct trading with each other, enabling them to finance their liquidity needs. In this context, they also possess the ability to closely and continuously monitor the prices offered by their competitors, thus gaining valuable insights into their pricing behaviours. We also assume that pricing strategies are subject to constant updates in response to changing market conditions.[507] The availability of these insights in real-time allows rival firms to adapt their own strategies and optimise their financial positions, including their inventories, accordingly. It is important to recognise the strategic implications under this scenario. We are in front of a dynamic environment where market participants assess and respond to the actions of their rivals in a repeated game. Thus, the continuous monitoring of competitors' pricing strategies empowers these firms to make informed decisions based on observed market behaviours, ultimately influencing their own pricing tactics.

In these market settings, we could argue that AI trading systems (e.g., based on DRL) might expose markets to the risks of 'tacit' collusion, given the presence of

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505 *See* Assad and others (n 448). The authors find evidence suggesting possible collusive behaviour in the German retail gasoline market, facilitated by the adoption of AI pricing software, which could result in tacit collusion among competitors.

506 *Cf*. Olivier Guéant and Iuliia Manziuk, 'Deep Reinforcement Learning for Market Making in Corporate Bonds: Beating the Curse of Dimensionality' (2019) 26 Applied Mathematical Finance 387, 388 <https://doi.org/10.1080/1350486X.2020.1714455> accessed 17 July 2024 developing an ensemble DRL strategy to solve market making problems such as determining the optimal bid and ask quotes across a large number of bonds.

507 *Cf*. World Bank, 'Electronic Trading Platforms in Government Securities Markets: Background Note' (November 2013) 20-22 <http://hdl.handle.net/10986/24098> accessed 17 July 2024, describing the most common pricing strategies employed by market makers, which can also trade among themselves to finance their liquidity positions and manage their inventories.

specific conducive market factors. Arguably, two or more competing AI systems could coordinate behaviour to attain supra-competitive price equilibria. Thanks to self-learning from direct trading interactions and observation of market price evolution, coordination would arise as a rational and optimal strategy. In this way, competing AI trading agents could autonomously solve the traditional game theory problem of coordination, all without any explicit communication. To illustrate this point, let us consider the example of the 'tit-for-tat' strategy, in which an agent cooperates on the initial move and then mirrors the strategy employed by its opponents, be it 'cooperation' or 'defection'.[508] Under this example, if competing AI trading agents—empowered by RL methods—could exploit a similar strategy, they could find means to coordinate their market behaviour without explicit communication. This would therefore lead to a scenario akin to algorithmic tacit collusion.

B. Financial benchmarks

Our second case study concerns the risks of algorithmic tacit collusion in 'financial benchmark'. Given their fundamental role as reference values for pricing numerous other financial assets,[509] many advanced jurisdictions have established specific legal frameworks to mitigate the risks of manipulation and collusion in financial benchmarks.[510] Traditionally, benchmark calculations were based on data provided by

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508 *See generally* Robert Axelrod and William D Hamilton, 'The Evolution of Cooperation' (1981) 211(4489) Science 1390 <https://doi.org/10.1126/science.7466396> accessed 17 July 2024, who demonstrate both theoretically and experimentally the superiority of this strategy. As is well known, the authors show, through a computer tournament, how cooperative behaviours based on reciprocity can arise in a social environment, evolve by interacting with other strategies, and become resilient once established.

509 *See, e.g.*, IOSCO, 'Financial Benchmarks' (January 2013) Consultation Report, CR01/13, 7-9 <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD399.pdf> accessed 17 July 2024.

510 For instance, the EU has introduced a specific regulation to protect financial benchmarks that came into effect on 1 January 2018 (i.e. the so-called EU Benchmark Regulation). *See* Regulation (EU) 2016/1011 of the European Parliament and of the Council of 8 June 2016 on Indices Used as Benchmarks in Financial Instruments and Financial Contracts or to Measure the Performance of Investment Funds and Amending Directives 2008/48/EC and 2014/17/EU and Regulation (EU) No 596/2014 [2016] OJ L 171/1.

contributing enterprises to a central authority. More recently instead, the prevailing approach is transaction-based benchmark calculation. Under the latter, financial benchmarks are determined by contributions based on specific market transactions made by a select group of major market participants.[511] Nevertheless, even under the new calculation regime, financial benchmarks could be an attractive target for algorithmic 'tacit' collusion.[512]

According to economic theory, in fact, competing firms may engage in benchmark rate fixing even when their business interests are not completely aligned. A research paper by *Boot, Klein, and Schinkel (2019)* demonstrates that collective forms of benchmark manipulation are theoretically possible. In particular, when rival firms are able to create and share inter-firm information, this can allow them to mitigate conflicts of interest related to their portfolio exposures. And if, at the same time, they can also engage in the manipulation of eligible transactions, benchmark-level collusion thus becomes possible.[513]

Presumably, with the widespread adoption of AI trading systems in financial benchmark markets, some of the technical and practical barriers to collusion may be relaxed. Increasingly capable AI trading systems could also find ways to coordinate their strategies autonomously without the explicit need for direct information sharing. For instance, thanks to sophisticated DL methods enabling powerful analytical capabilities and optimisations, algorithms might learn to coordinate their strategies

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511 *E.g.*, IOSCO (n 509) 17-18.

512 *See* Verstein (n 388) 217 and 250; *see also* Lilian Muchimba, 'Could Transaction-Based Financial Benchmarks be Susceptible to Collusive Behavior?' LVI(2) Journal of Economic Issues 362 <https://doi.org/10.1080/00213624.2022.2050152> accessed 17 July 2024.

513 *See* Nuria Boot, Timo Klein, and Maarten Pieter Schinkel, 'Collusive Benchmark Rates Fixing' (2019) Amsterdam Law School Legal Studies Research Paper No. 2017-34, 3-4 <https://ssrn.com/abstract=2993096> accessed 17 July 2024, demonstrating theoretically that collusion through benchmark rate fixing can be achieved when (i) colluding parties share information to adjust their respective exposures to benchmark rates ahead of the market and, at the same time, (ii) can engage in costly price manipulation of underlying assets in order to support the rate that maximises common profit.

just by observing market data feeds and interacting on electronic order books. Lastly, one could also speculate that increasingly advanced AI agents could independently develop new communication protocols. Exceeding human expectations, these new coordination tools might even go unnoticed by human experts, leaving markets in the hands of extremely capable algorithmic agents.

4.6 Conclusion

Considering the ongoing debate surrounding the algorithmic impact on market dynamics, this chapter has explored the potential of AI-powered trading systems to facilitate collusion within capital markets, whether 'explicit' or 'tacit'. While algorithmic systems can serve as potent tools for malicious entities seeking to engage in unfair market practices detrimental to markets and competition (i.e. explicit collusion), their burgeoning prevalence introduces novel and unprecedented risks of 'tacit' collusion.

Our comprehensive investigation, informed by both theoretical, empirical, and experimental literature, has unveiled that, under certain conducive market and technical conditions, AI trading agents may autonomously develop the capability to coordinate trading behaviour with rivals, thus resulting in outcomes resembling collusion. Notably, this novel form of algorithmic collusion may transpire without the need for algorithms to communicate with each other. Instead, algorithms iteratively arrive at supra-competitive equilibria through strategic transparency attained by their mere presence, observation, and interaction within market order books. This strategic coordination enables algorithms to uncover profitable strategies at the expense of market competitiveness.

While acknowledging that collusion risk may involve a wide range of algorithms, our focus has revolved around the intersection of (D)RL methods and algorithmic collusion. We therefore emphasised the independent collusion tendency of RL-based algorithmic trading agents. Their autonomous ability to engage in collusive behaviour without explicit human programming or guidance is particularly interesting. Noteworthy is the possible manifestation of these collusive risks in interactions with both algorithmic and human agents. However, identifying the likelihood of 'tacit' collusion poses a formidable challenge due to the unique characteristics of financial markets that make it a complex market environment. These markets embody a unique techno-socio-economic environment, markedly different from other digital marketplaces (e.g., online retail markets), which may be considered more prone to algorithmic forms of collusion.[514]

Nevertheless, while theoretically possible, the actual likelihood and scope of risks linked to algorithmic 'tacit' collusion necessitate further research. Considering various ML methods and market settings, such inquiries should aim to shed light on the practical and technical capabilities of AI agents in collusion and their consequential effects on market dynamics. Currently, regulatory authorities grapple with an expanding knowledge gap concerning algorithmic behaviour and interconnectedness, perilously constraining their ability to identify and address detrimental market practices made possible by innovation in algorithmic trading technology.

In sum, this complex landscape underscores the pressing need for regulatory bodies to proactively research how to effectively adapt and improve their competencies in dealing with algorithm-driven markets. As discussed in the subsequent chapters, one effective way to bridge this knowledge gap is to foster interdisciplinary collaboration between experts in Finance, Law, and Computer Science. By engaging in collaborative endeavours from different domains, financial regulators could synergise expertise and resources in order to facilitate the development of robust analytical frameworks and sophisticated tools to define, identify, and counter algorithmic forms of manipulation and collusion more effectively.

[514] *See, e.g.*, Assad and others (n 448).

PART II

CHALLENGES FOR MARKET ABUSE REGULATIONS AND GOVERNANCE OF ALGORITHMIC TRADING: EXPLORING PATHWAYS AHEAD

5. The EU Legal Framework for Algorithmic Market Manipulation and Governance of AI Trading

Rapid technological progress in algorithmic trading, due to ML, prompts us to critically evaluate the adequacy of existing law and regulation to ensure effective governance of the technology and its associated risks. Following our discussion of the novel risks of market manipulation and collusion introduced by AI trading, this chapter looks at the legal and regulatory framework in charge of promoting the safe and responsible use of trading technology as well as protecting market efficiency and integrity. Specifically, the aim is to provide a comprehensive analysis of both the EU anti-manipulation law and algorithmic trading regulation. This review will serve as the basis for the following chapters, in which we will address the ability of current legal regimes to meet the challenges arising from the rapid evolution of ML technology.

We begin by elucidating the scope of EU market abuse regulations applicable to algorithmic trading, with a specific focus on the prohibition of trading-based market manipulation (Chapter 5.1).[515] Next, we delve into the legal framework governing the enforcement of the prohibition of market manipulation, differentiating between administrative and criminal sanctioning regimes (Chapter 5.2). Moving forward, we turn to the regulatory aspects related to the governance of algorithmic trading, distinguishing between the rules applicable to investment firms and those intended for trading venues (Chapter 5.3). After that, we scrutinise the pivotal role that EU market conduct regulators play in the supervision of the market conduct of algorithmic trading (Chapter 5.4). Finally, we conclude with a summary of key findings (Chapter 5.5).

[515] We focus on this class of manipulation strategies as they turn out to be the natural scope for specific ML-based trading methods such as DRL-based trading agents.

5.1 The EU Anti-Manipulation Law for Algorithmic Trading

The EU's legal framework pertaining to the prohibition of market manipulation have entered its second generation.[516] Two main pieces of legislation set the 'rules of the game'. On one hand, the Market Abuse Regulation[517] (MAR) lays down a unified legal framework on the prohibition of market abuse across EU Member States.[518] On the other hand, the Market Abuse Directive[519] (MAD) supplements MAR by providing Member States with minimum harmonised rules for imposing criminal sanctions, specifically targeting the most serious cases of market manipulation. It is worth noting that the EU market abuse framework underwent significant reform in 2014. In part, this reform came in response to major market developments, such as the 2007-2008 global financial crisis, and the emergence of new risks introduced by technological advances in algorithmic trading.[520]

As we shall see, a close examination of the current legal regime reveals potential causes of regulatory ineffectiveness in addressing the additional risks posed by AI trading, especially due to ML. In what follows, we analyse the scope of the EU legal prohibition of market manipulation applicable to algorithmic trading.

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516 For a discussion of these policy developments, see Sofie Cools, 'Public Enforcement of the Market Abuse Regulation' in Marco Ventoruzzo and Sebastian Mock (eds), *Market Abuse Regulation: Commentary and Annotated Guide* (Oxford University Press 2017) 64-70.

517 Regulation (EU) No 596/2014 of the European Parliament and of the Council of 16 April 2014 on market abuse (market abuse regulation) and repealing Directive 2003/6/EC of the European Parliament and of the Council and Commission Directives 2003/124/EC, 2003/125/EC and 2004/72/EC [2014] OJ L173/1 [hereinafter MAR].

518 According to the EU taxonomy, market abuse includes economic wrong phenomena such as 'insider dealing' (MAR artt 8 and 14), 'unlawful disclosure of insider dealing' (MAR artt 10 and 14), and 'market manipulation' (MAR artt 12 and 15).

519 Directive 2014/57/EU of the European Parliament and of the Council of 16 April 2014 on criminal sanctions for market abuse (market abuse directive) [2014] OJ L173/179 [hereinafter MAD].

520 *See* MAR recital (38).

A. The prohibition of algorithmic market manipulation

At a very general level, various forms of market manipulation carried out through algorithmic trading, such as 'trade-based'[521] and 'order-based'[522] manipulation, are covered by Article 12 MAR. This legal provision defines market manipulation as a 'multi-layered' phenomenon.[523] Although it does not establish a uniform and comprehensive legal definition, Article 12 provides a list of trading activities and behaviours that the EU legislator explicitly deems detrimental to the integrity of EU capital markets. It is noteworthy that the EU MAR not only aims to deter traders from engaging in manipulative practices but also prohibits any mere attempt to do so.[524] It could thus be argued that EU MAR addresses the problem of deterrence of market manipulation at its core. In essence, the deterrent effect of the EU's anti-manipulation law seems to be strengthened by treating every manipulation scheme on an equal footing—i.e. regardless of actual economic success. As such, any attempt to distort the natural market forces of supply and demand or market prices is strictly forbidden and subject to punishment.

The most common manipulative algorithmic trading practices typically fall under the purview of Article 12(1)(a), which prohibits any trading behaviour—such as entering in a transaction, placing a trading order, or any other behaviour—that has or is likely to have either of the following effects:

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521 The term 'trade-based' manipulation refers to manipulative conducts that take place by simply buying and selling activities on a given financial instrument. *See* Allen and Gale (n 390) 505-506.

522 The term 'order-based' manipulation refers to those strategies leveraging relatively high rates of orders' submission, modification, and cancellation to deceive other market participants. *See* Dalko and Wang (n 369) 290-292.

523 Sebastian Mock, 'The Concept of Market Manipulation' in Marco Ventoruzzo and Sebastian Mock (eds), *Market Abuse Regulation: Commentary and Annotated Guide* (Oxford University Press 2017) 36.

524 *See* MAR art 15.

(i) deceiving other market participants by providing false or misleading signals regarding the natural forces of supply and demand for a specific financial instrument, or

(ii) fixing the price of one or more financial instruments at abnormal or artificial levels.

It follows that even in the context of algorithmic trading, the EU's anti-manipulation law prohibits strategies that aim to distort the natural market forces of supply and demand or market prices of financial instruments.[525] However, when algorithmic trading strategies employ deceptive techniques, fictitious devices, or other forms of contrivance, the aforementioned prohibition may overlap with that outlined in Article 12(1)(b).[526] As known, the latter provision specifically addresses the prohibition of 'information-based' forms of market manipulation.

Upon closer examination, however, the legal definition of market manipulation under MAR does not possess clearly delineated contours, potentially creating the risk of an uncertain legal prohibition.[527] In principle, the MAR's legal definition of market manipulation solely encompasses objective elements, suggesting that the EU legislator has adopted a strictly 'effects-based' definition.[528] In fact, for a particular trading

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525 It is important to note that the scope of application of the EU MAR legal regime excludes certain financial instruments. A well-known example includes so-called crypto-assets. The prohibition of market manipulation in these instruments was introduced in a new and specific regulation. *See* Regulation (EU) 2023/1114 of the European Parliament and of the Council of 31 May 2023 on markets in crypto-assets, and amending Regulations (EU) No 1093/2010 and (EU) No 1095/2010 and Directives 2013/36/EU and (EU) 2019/1937 [2023] OJ L150/40 [hereinafter MiCAR] art 91.

526 For a discussion on this issue, see Carsten Gerner-Beuerle, 'Article 12: Market Manipulation' in Matthias Lehmann and Christoph Kumpan (eds), *European Financial Services Law: Article-By-Article Commentary* (Nomos 2019) 748-750.

527 For more on the issue as well as regarding the ability of a trading behaviour to be 'likely' to create a market distortion, see ibid 735-736.

528 For a taxonomy of different regulatory approaches to the legal definition of market manipulation, see Avgouleas (n 297) 107-108.

behaviour to qualify as an administrative offence, it is sufficient for it to have a "likely" possibility of causing a market distortion. Yet, the law itself leaves us without clarification on the magnitude that such distortion ought to have in order to result in an offence. Further guidance is only provided by existing case law. Notably, with regard to the prohibition of fixing prices at abnormal or artificial levels, the temporal extent of market distortion is considered irrelevant *per se*.[529] The interpretation offered by the Court of Justice of the European Union (CJEU) appears somewhat to contribute to enhanced legal certainty, particularly with respect to algorithmic trading strategies that, due to their lightning-fast nature, can impact the fair and orderly functioning of markets even for very short durations.

While the MAR's legal definition of market manipulation encompasses relatively interpretable objective elements, it does not entail any subjective ones. Unlike the criminal prohibition under MAD,[530] the administrative offence of market manipulation, at least in principle, does not rely on the specific intention of the manipulator to distort natural market conditions.[531] The absence of a subjective element, coupled with a somewhat ambiguous wording of the objective element, may lead to a lack of predictability and legal certainty, potentially undermining the ability of law enforcement to deal with algorithmic forms of market manipulation. Indeed, distinguishing between legitimate and unlawful trading activities can often result in a puzzling task.[532] To ascertain instances of manipulation and attribute liability for misconduct, thus, a comprehensive assessment of the actual motivations behind a

[529] *See* Case C-445/09, IMC Securities BV v Stichting Autoriteit Financiële Markten [2011] ECR I-05917, paras 26-27.

[530] *See* MAD art 5.

[531] *See* Gerner-Beuerle (n 526).

[532] *See, e.g.*, Fischel and Ross (n 364) 544-545. This influential and often-cited paper in the legal scholarship posits that due to the intricate challenge of discerning the true intentions underpinning a specific trading activity solely from market observations, coupled with the inherent high risks associated with engaging in market manipulation, the law should not explicitly address this phenomenon.

given algorithmic trading behaviour is typically necessary.[533] As will be discussed in Chapter 7.3, one approach to accomplish this is by inferring manipulative intent from trading patterns observed thanks to ML-powered market surveillance systems. But this presupposes that supervisors are equipped with appropriate technology to detect suspicious activities and rely on accepted statistical methodologies to effectively recognise and clearly differentiate various manipulative strategies from lawful activities.

In an effort to elucidate instances that pose a significant threat to the integrity of EU capital markets, Article 12(2) provides a non-exhaustive list of examples of market manipulation. Hence, algorithmic traders must be aware that specific trading strategies, such as 'abusive squeeze'[534] or 'banging the close'[535], are already well understood and clearly defined by the EU legislator. In addition, the EU's anti-manipulation law directly targets certain forms of disruptive and manipulative behaviour facilitated by advanced trading technology, including HFT strategies like 'spoofing'.[536]

It is noteworthy that Article 12 must be read in conjunction with MAR Annex I, which outlines a range of indicators that should be considered in assessing a possible violation of market manipulation. Whenever these indicators are met, they may give rise to a presumption of manipulation.[537] Additionally, under Article 12(5) of MAR, the

533 Gerner-Beuerle (n 526) 736.

534 The term 'abusive squeeze' refers to those behaviours involving the abuse of a dominant position aimed at significantly distorting the price at which other participants are obliged to trade in order to fulfil their contractual obligations in relation to the underlying financial instrument. *See* MAR art 12(2)(a).

535 The term 'banging the close' refers to practices involving the massive buying/selling of a particular financial instrument just before the close of the trading day, often to benefit from an even larger position in a derivative contract that is cash-settled based on the price of the same financial instrument on that day. *See* MAR art 12(2)(b).

536 *See* MAR art 12(2)(c).

537 MAR art 12(3).

European Commission has used its regulatory powers to amend Annex I with a delegated act that provides a more detailed, albeit non-exhaustive, list of technical indicators to assist competent authorities in identifying and evaluating suspected instances of market manipulation.[538]

Overall, while the EU legal definition of market manipulation certainly aims to combat manipulative trading practices involving algorithms, it may fall short in providing adequate legal certainty. Particularly concerning more sophisticated forms of AI-optimised market manipulation, one might question whether a rather vague legal definition, which allows for considerable legal interpretation, can effectively regulate these activities. Unlike manipulative strategies of more 'analogue' times, in fact, cases of manipulation by AI trading increase the burden on law enforcement authorities to succeed in prosecution. In today's algorithm-dominated markets, law enforcement agencies are faced with the challenge of presenting documented evidence to prove the true motives behind suspicious trading activities or, at the very least, establish the negligent use of algorithmic trading in order to successfully prosecute misconduct.

5.2 Liability Framework and Sanctions Regime

The EU MAR+MAD legal framework establishes a 'dual track' liability system for market manipulation. This system operates by differentiating between administrative and criminal liability based on the gravity of the offence committed in violation of market conduct rules. Consequently, the assessment of such violations requires meticulous case-by-case examination. In the following, we delve into these two distinct regimes highlighting their key features and implications for law enforcement.

[538] *See* Commission Delegated Regulation 2016/522 of 17 December 2015 supplementing Regulation (EU) No 596/2014 of the European Parliament and of the Council as regards an exemption for certain third countries public bodies and central banks, the indicators of market manipulation, the disclosure thresholds, the competent authority for notifications of delays, the permission for trading during closed periods and types of notifiable managers' transactions [2016] OJ L 88/1. It should be noted that the European Commission has the competence to correct and update the list of technical indicators of market manipulation to take into account technological innovation and market developments.

A. Administrative liability and sanctions

Violations of MAR prohibitions give rise to administrative liability and are enforced by the 'national competent authorities' (NCAs) of EU Member States within their respective jurisdictional competence.[539] Administrative liability can be attributed to both individuals, such as human traders or their bosses, and legal persons, such as investment firms. In the case of legal persons, liability may extend to every natural person within an organisation who participate in the decision to engage in conducts prohibited by MAR.[540] Similar to prohibition of insider dealing[541], this provision applies to legal persons, their agents, and other natural persons acting on behalf of a legal person.[542]

Determining whether a natural person, such as an employee, is acting on behalf of a legal person is contingent upon the legal systems of EU Member States,[543] specifically the national rules pertaining to agency in labour and criminal law.[544] Generally, the notion of "acting on behalf" encompasses any natural person who possesses powers of legal representation, the authority to make decisions on behalf of a legal person, or the ability to exercise control within a legal person.[545] Although individual responsibilities and duties are generally well-defined within private organisations such as investment firms, attributing liability for misconduct by a given

539 *See* MAR art 22.

540 MAR art 12(4).

541 For a legal definition of 'insider dealing', see MAR art 8.

542 Gerner-Beuerle (n 526) 757.

543 MAR art 8(5).

544 *See* Carsten Gerner-Beuerle, 'Article 8: Insider Dealing' in Matthias Lehmann and Christoph Kumpan (eds), *European Financial Services Law: Article-By-Article Commentary* (Nomos 2019) 705.

545 *Cf*. MAD art 8(1).

algorithmic trading system, particularly when sophisticated AI approaches are involved, can be challenging.

Article 30 of MAR addresses administrative violations of market abuse and defines the minimum harmonised range of administrative sanctions and other legal measures available to NCAs.[546] EU Member States, however, retain discretion in adopting administrative sanctions for infringements listed in Article 30(1)(a),[547] as well as for non-compliance or failure to cooperate with an investigation, inspection, or request, as stipulated by Article 23(2) MAR[548],[549] if they already subject the same violation to criminal sanctions. If a Member State opted for criminal penalties for MAR

546 Pursuant to Article 30(2) of MAR, each Member State is required to confer upon or make available to the respective NCA the power to impose a number of 'minimum harmonised' administrative sanctions and other measures against violations of market manipulation. Those include: (a) ordering to cease unlawful behaviours; (b) ordering the disgorgement of profits or avoided losses; (c) issuing a public warning; (d) the withdrawal or suspension of authorisation to provide financial services; (e) ordering the ban of managerial or other responsibilities within an investment firm; (f) imposing administrative pecuniary sanctions.

547 Specifically, administrative sanctions must be available, inter alia, in the event of market manipulation (MAR art 15) but also for ineffective prevention and detection of market manipulation (MAR art 6(1)) and failures to effectively report orders and transactions that could amount to market manipulation (MAR art 16(2)).

548 According to Article 23(2) of MAR, each NCA should enjoy "at least" a number of supervisory and investigatory powers, including: (a) accessing any document and data in any form and receiving or taking a copy of those; (b) requiring or demanding information from any persons and their principals by, if necessary, summoning and questioning those persons to obtain such information; (c) requesting information, obtaining reports on transactions, and obtaining direct access to trading systems in relation to commodity derivatives; (d) carrying out on-site inspections and investigations; (e) entering the premises of natural and legal persons to seize documents or data that may be relevant for inspection or investigation to prove an infringement of market manipulation; (f) referring matters for criminal investigations; (g) requiring existing recordings of telephone conversation and other electronic communications or data traffic records; (h) requiring, to the extent that is permitted under national law, existing data records from telecommunications operators for investigations where there is a reasonable suspicion of infringements; (i) requesting the freezing or sequestration of assets, or both; (j) suspending trading of the financial instrument concerned; (k) requiring the temporary cessation of any practice contrary to MAR; (l) imposing a temporary prohibition on the exercise of professional activity; and (m) taking all necessary measures to ensure that the public is correctly informed about the abusive practice.

549 MAR art 30(1)(b).

violations by 3 July 2016, it is not obligated to apply any of the administrative sanctions.[550]

As a general rule, however, both administrative and criminal sanctions can be applied concurrently, provided that the administrative proceedings are not of a criminal nature. Nonetheless, if a Member State imposes both administrative and criminal sanctions for the same infringement, it must ensure consistency between the two alternatives while respecting the principles of '*ne bis in idem*'[551] in criminal law,[552] as well as the 'right to a fair trial'[553].[554]

B. Criminal liability and sanctions

With the latest reform of European market abuse legislation, MAD has introduced a set of common minimum rules on criminal liability and corresponding sanctions for market manipulation. Specifically, Article 5 MAD mandates that EU member states must take all necessary measures to ensure that market manipulation constitutes a criminal offence, particularly in cases of serious misconduct and intentional wrongdoing.[555] Under the new regime, the MAD not only criminalises the act of market

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550 MAR art 30(1) subpara 2.

551 According to this principle, a person cannot be criminally prosecuted for the same facts for which he or she has already been finally convicted or acquitted in an administrative proceeding. For a recent research paper on the legal challenges for EU courts in the application of the 'ne bis in idem' principle in relation to financial crimes, see Marina Matić Bošković and Jelena Kostić, 'The Application of the *Ne Bis In Idem* Related to Financial Offenses in the Jurisprudence of the European Courts' (2020) 25(2) NBP Journal of Criminalistic and Law 67 <https://doi.org/10.5937/nabepo25-27224> accessed 17 July 2024.

552 *See* Grande Stevens et al v Italy (App Nos 18640/10, 18647/10, 18663/10, 18668/10 and 18698/10), ECtHR, 7 July 2014, paras 221- 228.

553 *See* Convention for the Protection of Human Rights and Fundamental Freedoms (European Convention on Human Rights, as amended) art 6 <https://www.echr.coe.int/documents/d/echr/Convention_ENG> accessed 17 July 2024.

554 *See, e.g.*, Matteo Gargantini, 'Public Enforcement of Market Abuse Bans. The ECtHR Grande Stevens Decision' (2015) 1 Journal of Financial Regulation 149 <https://doi.org/10.1093/jfr/fju007> accessed 17 July 2024.

555 MAD art 5(1). It should be noted, however, that this provision does not define when a case of manipulation is "serious", which is specified only by MAD recital (12). The latter states that:"*[M]arket*

manipulation itself but also the incitement, aiding and abetting of such manipulative practices,[556] as well as attempts thereof.[557] Furthermore, the MAD regime extends criminal liability to cases where a lack of supervision or control has facilitated the occurrence of market manipulation.[558]

Although the legal definition of market manipulation provided by MAD largely aligns with that of MAR, there exist significant differences in their application due to the enhanced procedural safeguards offered by Member States' criminal codes. In the context of criminal law, any alleged manipulative conduct must result in an *actual* and demonstrable adverse effect on the natural market forces of supply and demand or market prices in order to qualify as a criminal offence. Unlike the administrative prohibition, the assessment under criminal law requires to show a certain and tangible impact on markets, rather than mere possibilities.[559] Consequently, the criminal offence requires a higher standard of evidence and burden of proof, namely the 'beyond a reasonable doubt' standard, as opposed to the 'preponderance of the evidence' one. However, as in the case of administrative proceedings, one possible line of defence available to traders and investment firms is to prove that the alleged conduct is

manipulation should be deemed to be serious in cases such as those where the impact on the integrity of the market, the actual or potential profit derived or loss avoided, the level of damage caused to the market, the level of alteration of the value of the financial instrument or spot commodity contract, or the amount of funds originally used is high or where the manipulation is committed by a person employed or working in the financial sector or in a supervisory or regulatory authority."

556 MAD art 6(1).

557 MAD art 6(2).

558 MAD art 8(2).

559 Carsten Gerner-Beuerle, 'Market Abuse Directive (MAD) - Article 6: Inciting, aiding and abetting, and attempt' in Matthias Lehmann and Christoph Kumpan (eds), *European Financial Services Law: Article-By-Article Commentary* (Nomos 2019) 635.

legitimate[560] or conforms to 'accepted market practices'.[561] Furthermore, defendants can also avail themselves of traditional types of defence offered by Member States' criminal law rules,[562] including exercising their fundamental rights of defence.[563]

In accordance with the enforcement regime outlined by the MAD, criminal sanctions against market manipulation must be "effective, proportionate and dissuasive".[564] Even in cases where market manipulation occurs through algorithmic trading strategies, EU member states are obligated to ensure that such conduct can be punishable by imprisonment for a maximum term of four years.[565] Additionally, the MAD recognises not only 'individual criminal liability' against natural persons, but also provides for 'corporate criminal liability' against legal persons. As stipulated by Article 8(1) MAD, legal persons can be held accountable for offences committed for their benefit by one or more of their employees, acting either individually or as part of the organisation's decision-making body. In other words, investment firms cannot in principle escape criminal liability when it comes to the malevolent use of trading

560 *See* ibid 636, stating that "*[b]ehaviour is carried out for a legitimate reason if it pursues a goal that is in line with the principles, structures, and mechanisms underpinning the operation of capital markets and is not detrimental to transparency, stability, and market integration in the EU*".

561 Demonstrating that a conduct falls among an 'accepted market practice' by an NCA is a real line of defence for investment firms. The legal framework of 'accepted market practice' is provided by MAR art 13.

562 *See generally* Samuli Miettinen, *Criminal Law and Policy in the European Union* (Routledge 2012) 133-138. For a theory of criminal liability applied to AI crime addressing the applicability of traditional types of defence under criminal law, see Gabriel Hallevy, *Liability for Crimes Involving Artificial Intelligence Systems* (Springer Cham 2015) 150-184 <https://doi.org/10.1007/978-3-319-10124-8> accessed 17 July 2024.

563 For a discussion of the legal scope of the rights of defence as an EU fundamental right, see Herwig CH Hofmann, Gerard C Rowe, and Alexandre H Türk, *Administrative Law and Policy of the European Union* (Oxford University Press 2011) 204-221 <https://doi.org/10.1093/acprof:oso/9780199286485.001.0001> accessed 17 July 2024.

564 MAD art 7(1).

565 MAD art 7(2). Note that Member States are free to set harsher penalties provided the latter respect the proportionality principle as stipulated in Article 7(1) of MAD. More precisely, the maximum length of a prison term or the amount of a pecuniary fine must reflect the profits made or losses avoided, the damage caused to other market participants, and the impact of the offence on the smooth and fair functioning of markets. *See* Gerner-Beuerle (n 559) 640.

algorithms on their behalf. However, it can be a considerable challenge for law enforcement authorities to ascertain the true motives and responsibilities behind the misbehaviour of a particular algorithmic trading system.

C. The problem of 'divided interpretation' and regulatory arbitrage

Despite the ongoing convergence of market abuse regulatory regimes among Member States, the persistence of regulatory arbitrage is still a real risk. This is especially true given the presence of highly complex manipulative strategies based on artificial intelligence, allowing malicious agents to undermine market integrity without taking great risk of sanction. Notwithstanding the primary policy objective of the EU MAR+MAD framework to establish a "fair, strong and deterrent sanction regime"[566] for Member States, there may be risks that legal prohibitions are implemented unevenly and inconsistently across the EU particularly given persistent differences between national laws. This problem is known as 'divided interpretation'.[567]

At least in principle, the EU legal framework allows for both public and private enforcement of market conduct rules.[568] Nevertheless, private enforcement of financial law is not extensively developed in the EU, especially when compared to the United States, where private enforcement of market abuse has historically played a more prominent role.[569] As the EU legal framework does not directly address civil liability for

566 MAD recital (38).

567 *See* Sebastian Mock, 'History, Application, Interpretation, and Legal Sources of the Market Abuse Regulation' in Marco Ventoruzzo and Sebastian Mock (eds), *Market Abuse Regulation: Commentary and Annotated Guide* (Oxford University Press 2017) 9.

568 For an account on the role of private enforcement of EU financial laws and its relationship with public enforcement, see Danny Busch, 'The Private Law Effect of MiFID: The Genil Case and Beyond' (2017) 13 European Review of Contract Law 70 <https://doi.org/10.1515/ercl-2017-0003> accessed 17 July 2024.

569 *See* John C Coffee, 'Law and the Market: The Impact of Enforcement' (2007) 156 University of Pennsylvania Law Review 229, 245 <https://scholarship.law.columbia.edu/faculty_scholarship/1462> accessed 17 July 2024.

market manipulation,[570] our focus here primarily centres on liability issues arising from the problem of 'divided interpretation' within the realms of administrative and criminal law.[571]

On the one hand, the existing discrepancies in the administrative law of Member States may lead to unequal legal treatment of market manipulation due to compliance with constitutional guarantees and other legal restrictions imposed on the activities of administrative authorities.[572] On the other hand, the legal treatment of the 'intent' requirement as a basis for liability in the criminal (and civil) law of Member States also lacks uniformity.[573] In this regard, the literature argues that issues specific to the legal interpretation of the intent requirement should be resolved within the legal context of the respective sanction. Therefore, since administrative liability for market manipulation under MAR does not explicitly require proof of the intent of manipulators, it is left to the administrative codes of Member States to address this interpretive challenge.[574] For instance, in certain Member States, like Italy, the threshold for the attribution of administrative liability for market manipulation is established through a fault-based test.[575] In contrast, criminal liability is regulated by

570 *See* Mock (n 63) 44.

571 For a discussion of Member States' national laws on civil liability, see Alexander Sajnovits, 'The Market Abuse Regulation and the Residual Role of National Law' (2023) European Banking Institute Working Paper Series 2023 – no. 137 <https://ssrn.com/abstract=4392675> accessed 17 July 2024.

572 Mock (n 104) 8.

573 Mock (n 63) 41.

574 The same principle applies to civil liability for market manipulation. *See* ibid 42.

575 *See* Carlo Enrico Paliero, '"Market Abuse" e Legislazione Penale: Un Connubio Tormentato' (2005) 7 Il Corriere del Merito 809, 810 <https://edicolaprofessionale.com/bd/rivisteI0RW/40/540/7832540_MERIT_00134991_2005_07_0809.pdf> accessed 17 July 2024; Enrico Amati, *Abusi di Mercato e Sistema Penale* (Giappichelli Editore 2012) 255-257 and 303-304 <https://discrimen.it/wp-content/uploads/Amati-Abusi-di-mercato-e-sistema-penale.pdf> accessed 17 July 2024; Marco Ventoruzzo, 'When Market Abuse Rules Violate Human Rights: Grande Stevens v. Italy and the Different Approaches to Double Jeopardy in Europe and the US' (2015) 16 European Business Organization Law Review 145, 150 <https://doi.org/10.1007/s40804-015-0002-2> accessed 17 July 2024.

the criminal codes of Member States, as the MAD text itself does not provide a specific framework for the intent requirement.[576]

Given the aforementioned disparities in the legal treatment of market manipulation liability among Member States, EU capital markets lack a level playing field in the definition of market manipulation, making them vulnerable to 'regulatory arbitrage'. This disparity situation may pose a significant challenge to effective law enforcement in the EU against more sophisticated market manipulation strategies that often have cross-border implications. It is worth noting, however, that while this issue is also relevant to traditional—hence non-AI trading—forms of market manipulation, the more advanced, AI-optimised manipulative strategies further exacerbate enforcement concerns. This is mainly because AI trading enjoys greater capabilities, including a potentially ubiquitous market activity across EU capital markets.

5.3 The Governance of Algorithmic Trading and Market Conduct

After the analysis of the legal prohibitions of market manipulation under EU law, our attention now turns to the regulation of algorithmic trading—a crucial aspect in governing risks for the fair and orderly functioning of markets.

The EU regulatory framework adopts a *behaviouristic* approach aimed at ensuring investment firms' compliance with regulatory expectations in their use of trading algorithms. Under this approach, algorithmic behaviour is evaluated on the basis of objective and measurable outcomes and their effects on markets.[577] So to speak, then, this approach represents an 'outcome-based' form of regulation.[578] In fact, EU regulators maintain a relatively *neutral* stance towards the specific AI technology,

[576] *See* MAD recital (21).

[577] *See, e.g.*, Seyfert (n 98) 1543.

[578] For a critical account of the limits of 'outcome-based' regulatory approaches, see Cary Coglianese, 'The Limits of Performance-Based Regulation' (2017) 50(3) University of Michigan Journal of Law Reform 525 <https://repository.law.umich.edu/mjlr/vol50/iss3/1> accessed 17 July 2024.

particularly ML methods, employed by market participants. Simultaneously, they impose specific organisational requirements to enable firms to identify and mitigate risks that may arise from their algorithmic trading activities. However, the efficacy of these measures underscores the critical requirement for investment firms to effectively understand, control, and predict the market behaviour and outcomes of their trading systems.[579]

The set of legal obligations and regulatory requirements related to algorithmic governance is primarily governed by the EU Markets in Financial Instruments Directive II[580] (MiFID II), which is complemented by the Markets in Financial Instruments Regulation[581] (MiFIR).[582] Complementary to MiFID II/MiFIR legal provisions, the MAR legal regime includes specific provisions regarding the prohibition of algorithmic market manipulation, as discussed above. Overall, this substantial set of rules serves a dual purpose. First, they seek to mitigate knowledge disparities—commonly referred to as 'information asymmetry'—between industry participants and financial regulators.[583] By doing so, these rules aim to safeguard adequate levels of transparency. Second, these provisions are designed to guide investment firms towards the safe and reliable adoption of trading technology. They achieve this objective, for instance, by assisting firms in identifying practices that could potentially introduce risks to the fair, transparent, and orderly functioning of capital markets.[584] Consequently, these set of

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579 *See, e.g.*, Seyfert (n 98) 1546-1550.

580 Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments [2014] OJ L 173/349 [hereinafter MiFID II].

581 Regulation (EU) No 600/2014 of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments [2014] OJ L 173/84 [hereinafter MiFIR].

582 Both pieces of legislation are further supplemented by relevant EU legislation.

583 *See, e.g.*, Myklebust (n 87) 394-395.

584 *See, e.g.*, Trude Myklebust, 'Fairness and Integrity in High-Frequency Markets – A Critical Assessment of the European Regulatory Approach' (2020) 31(1) European Business Law Review 33, 58-64 <https://doi.org/10.54648/eulr2020003> accessed 17 July 2024.

rules serve as a compass, guiding investment firms towards responsible conduct and safeguarding the integrity of market operations.

In the fight against algorithmic market manipulation and other forms of market disruption, the enforcement of EU financial law and regulation is based on a comprehensive approach that encompasses both *ex-ante* and *ex-post* regulatory tools. These tools are applied within a multi-layered institutional architecture involving various actors at different enforcement levels, resulting in a regime that relies on three distinct and complementary 'lines of defence'.[585]

The 'first line of defence' comprises investment firms actively involved in algorithmic trading or providing 'direct electronic access'[586] (DEA) services. Investment firms themselves play indeed a vital role in mitigating potential risks to markets arising from their use of algorithmic trading by adhering to regulatory requirements and implementing effective control systems. In this manner, they act as first-line protectors against potential misconduct, ensuring that the market conduct of their algorithms aligns with the established regulatory standards.

The 'second line of defence', located at an intermediate level, lies with regulated trading venues that offer electronic trading services. Entrusted with specific delegated regulatory responsibilities, trading venues play a crucial gatekeeping role, striving to ensure fair and orderly markets. Through diligent market surveillance and monitoring mechanisms, they are called upon to cooperate with financial supervisors to proactively

585 The term 'three lines of defence' generally refer to the three internal functions of investment firms that together work to ensure effective governance of model risks in algorithmic trading. These functions include (i) the staff and division that use algorithmic systems on a daily basis, (ii) those responsible for risk management and regulatory compliance, as well as (iii) both internal and external auditors. *See, e.g.*, Isabella Arndorfer and Andrea Minto, 'The "Four Lines of Defence Model" for Financial Institutions' (December 2015) BSI, Financial Stability Institute Occasional Paper No 114-7 <https://www.bis.org/fsi/fsipapers11.pdf> accessed 17 July 2024. For the purpose of this dissertation, however, the term is used to refer to the various actors involved, at different levels, in the governance of the risks to market integrity associated with algorithmic trading.

586 More precisely, there are two distinct types of DEA, namely 'direct market access' and 'sponsored access'. For a legal definition, see MiFID II art 4(1)(41).

address any suspicious trading activities that may ultimately jeopardise market integrity.

Finally, the 'last line of defence' involves EU financial supervisors, including Member States' national competent authorities, aided at the supranational level by the European Securities Markets Agency (ESMA). The collective efforts of NCAs, combined with ESMA's expertise and coordinating role, contribute to safeguarding the integrity of EU capital markets. Through their regulatory oversight and use of enforcement powers, these institutions form the EU supervisory framework responsible for detecting and deterring market abuse.

In the remainder of this section, we will delve into the specific contributions of the first two lines of defence: (A) investment firms and (B) trading venues. Subsequently, we will dedicate a separate section to thoroughly examine the critical role played by EU financial supervisors in maintaining market integrity (Chapter 5.4).

A. The 'first line of defence': i.e. investment firms

As the best party positioned to manage risks associated with their use of algorithmic trading, investment firms represent the 'first line of defence' against market manipulation and other disruptive trading activities. To this end, Article 17 MiFID II lays down legal and organisational requirements for investment firms, with additional provisions specifically addressing those players engaging with HFT and market making. There requirements are further elaborated upon in regulatory technical standards developed by ESMA (i.e. RTS 6[587]) and supplemented by the MAR prohibition on algorithmic market manipulation.

587 Commission Delegated Regulation (EU) 2017/589 of 19 July 206 supplementing Directive 2014/65/EU of the European Parliament and of the Council with regard to regulatory technical standards specifying the organisational requirements of investment firms engaged in algorithmic trading (2016) OJ L 87/417 [hereinafter RTS 6].

Collectively, these legal provisions are designed to foster the development and use of algorithmic trading systems and strategies in a trustworthy manner. Accordingly, investment firms are subject to both *ex-ante* and *ex-post* regulatory requirements, which aim to steer trading behaviour towards fair and socially acceptable market practices.[588] As noted in scholarly literature, the EU's approach to regulating algorithmic trading places emphasis on testing and the concept of 'human-in-the-loop-and-control'. This approach ensures that trading algorithms are subjected to proper auditing and oversight, maintaining a proper level of human involvement to mitigate potential risks associated with automated trading.[589] The overarching goal of these regulatory measures is to create an environment where algorithmic trading can flourish within the boundaries of responsible and ethical conduct, promoting fair and transparent market practices.[590]

i. Ex-ante regulatory requirements

From an *ex-ante* perspective, the regulatory requirements outlined in MiFID II aim to instil trust and confidence in the realm of algorithmic trading. These requirements operate on two fronts: (i) promoting transparency and (ii) ensuring the development and use of trading technology in a safe, responsible, and legally compliant manner. In this regard, we explore below the significance and impact of 'disclosure requirements' and the process of 'testing' algorithms in mitigating the risks associated with algorithmic misbehaviour.

- *Disclosure requirements*

[588] *See, e.g.*, Lee and Schu (n 85); Myklebust (n 87); Gerner-Beuerle (n 89).

[589] *See, e.g.*, Lee and Schu (n 85).

[590] *Cf.* Ricky Cooper, Michael Davis, and Ben Van Vliet, 'The Mysterious Ethics of High-Frequency Trading' (2016) 26(1) Business Ethics Quarterly 1 <https://doi.org/10.1017/beq.2015.41> accessed 17 July 2024; Myklebust (n 584).

When investment firms engage in algorithmic trading, they become subject to various 'disclosure requirements'. As part of market access regulation, under Article 17(2) MiFID II, investment firms must notify their use of algorithmic trading both to their home NCA and the NCAs of the Member States where the trading venues in which they operate are located. In general, home-country NCAs possess extensive powers, enabling them to access information on algorithmic trading regularly or on an *ad hoc* basis. This includes gaining insights into the functioning of algorithmic trading systems and strategies, as well as the associated compliance and risk management controls. Any information gathered can be shared among NCAs, facilitating their supervisory responsibilities within their respective jurisdictional competence.[591]

Ideally, these powers should empower financial supervisors to obtain any necessary information to ensure effective supervision of compliance by investment firms. However, the productive use of such information relies heavily on NCAs' ability to comprehend it. It should not be assumed that supervisors can effortlessly grasp the intricacies of sophisticated and complex approaches to algorithmic trading. Whenever algorithmic trading leverages ML methods, this requires supervisors to acquire adequate knowledge to effectively navigate their technical specificities and associated risks. However, when faced with self-learning algorithms that dynamically reprogram themselves—such as in DRL-based systems—, it is unclear what level of details supervisors can actually access due to the black box problem. Indeed, the same developers and users of ML-powered trading systems may also find it challenging to fully comprehend the inner workings of their opaque algorithms.[592]

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591 *Cf.* MiFID II art 17(2); *see also* Raschner (n 88).

592 *Cf.* Adrien Bibal and others, 'Legal Requirements on Explainability in Machine Learning' (2021) 29(2) Artificial Intelligence and Law 149 <https://doi.org/10.1007/s10506-020-09270-4> accessed 17 July 2024, arguing that EU supervisors have broad powers to access the details of algorithmic trading systems, including substantial information on ML models and parameters; *see also* Raschner (n 88).

- *Testing*

MiFID II places significant emphasis on the testing of trading algorithms to ensure their development and use in a trustworthy manner. Present auditing frameworks encompass two key types of testing: (i) 'behavioural testing', as outlined in Articles 5 and 7 RTS 6, and (ii) 'conformance testing', as stipulated in Article 6 RTS 6.

'Behavioural testing' is a *de jure* requirement that must be conducted prior to the initial deployment or substantial update of a given trading algorithm.[593] In order to fulfil this requirement, investment firms need to establish well-defined methodologies for the development and testing of their trading systems. These methodologies encompass crucial aspects related to, for instance, the design, performance, recordkeeping, approval, and accountability of involved individuals.[594] The testing methodologies employed must be tailored to the specific techno-economic market environment in which algorithmic trading is implemented. Additionally, whenever there is a substantial modification or update to the functioning of the algorithms or changes in market access, further testing is also *de jure* mandated.[595] In essence, compliance with these regulatory requirements aims to ensure that algorithmic trading:

(i) does behave as intended;

(ii) adheres to EU market conduct rules;

(iii) complies with the rules of trading venues; and

593 RTS 6 art 5(1).

594 RTS 6 art 5(3).

595 RTS 6 art 5(5).

(iv) does not contribute to disorderly trading conditions, keep working in an effective way even in stressed market conditions and, if necessary, can be halted through the implementation of kill-switch functionality.[596]

As per the current regulatory framework, all such testing activities must exclusively take place within simulated environments rather than real markets.[597] Investment firms have the option to conduct these tests using their own facilities or utilise those provided by trading venues, DEA providers, or third-party vendors.[598] Without prejudice to the general framework on 'conformance testing' that specifies *how* and *when* the algorithms should be tested,[599] however, investment firms bear full responsibility for testing its own trading systems.[600] 'Conformance testing' serves the purpose of assessing the operational compatibility and resiliency of algorithmic trading when operating within a specific trading venue.[601] It is therefore intended mainly to ensure that algorithmic trading systems align with the operational requirements of trading venues.

Furthermore, prior to the actual deployment of a trading algorithm, certain pre-set limits must be established. These limits encompass factors such as:

(i) the range of financial instruments eligible for trading;

(ii) parameters related to the price, value, and number of orders;

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596 *See* RTS 6 art 5(4).

597 RTS 6 art 7(1).

598 RTS 6 art 7(2).

599 *See* RTS 6 art 6, specifying the specific circumstances under which investment firms are required to perform conformance testing, as well as the basic element that such testing activity must entail.

600 RTS 6 art 7(3).

601 *See, e.g.*, Patrick Raschner (n 86) 4.

(iii) the specific trading strategy pursued; and

(iv) the number of trading venues in which the algorithm will operate.[602]

By setting these predefined limits, investment firms aim to provide a clear framework for the functioning of trading algorithms and their operational boundaries. Although some may contend that existing testing frameworks are able to address the risks to market integrity linked to AI trading,[603] there are some reasons to believe that financial regulators ought to consider the necessity of furnishing additional guidance to industry participants for better control over sophisticated forms of market manipulation, such as spoofing.[604] Indeed, additional guidance may foster legal certainty by providing market participants with more precise legal boundaries within which to implement their algorithmic strategies. We will return to this topic later in this chapter.

Given the current regulatory approach to algorithmic governance, there is a potential risk that investment firms will engage predominantly in 'back-testing' the performance of their trading algorithms. In doing so, however, they may be neglecting due consideration of the potential risks of disorderly trading and even market abuse. This problem becomes particularly evident in the case of increasingly autonomous trading algorithms that rely on ML methods—particularly DRL applications. These concerns seem further compounded when mitigating market manipulation risks necessitates advanced tools and substantial investment in control system technology. From a different perspective, it could be argued that existing 'behavioural testing'

[602] RTS 6 art 8.

[603] *Cf.* Peter Georg Pitch and Gaspare Tazio Loderer, 'Framing Algorithms: Competition Law and (Other) Regulatory Tools' (2019) 42(3) World Competition 391 <https://www.zora.uzh.ch/id/eprint/181193> accessed 17 July 2024, taking the view that the EU regulatory approach to algorithmic trading may serve as model for regulating algorithms in other economic law contexts.

[604] *See, e.g.*, Fletcher (n 75); Barr and others (n 344); Cartea and others (n 345).

regimes may impede firms from deploying autonomous AI trading systems, such as those based on DRL, as these applications dynamically evolve over time in response to trading experiences, rendering their market behaviour less predictable.[605]

ii. Ex-post regulatory measures

From an *ex-post* point of view, instead, investment firms are required to establish 'internal control' functions (e.g., risk management and regulatory compliance) that must align with the nature and scope of their trading strategies, as well as the associated risks.[606] In addition, investment firms must ensure effective and continuous monitoring of all trading activities executed through their systems, employing 'automated surveillance systems',[607] and support supervisory actions by promptly submitting 'suspicious transaction and order reports' (STORs) when operating as a trading venue.[608]

- *Internal controls*

Investment firms are obligated to implement a range of risk and compliance management tools, including 'pre-trade' control mechanisms,[609] 'real-time monitoring'

[605] *See, e.g.*, Gerald Spindler (n 92) 217-218; Raschner (n 86) 29-32.

[606] *Cf.* RTS 6 art 1.

[607] *See* RTS 6 art 13.

[608] *See* MAR art 16.

[609] 'Pre-trade' controls (i.e., quantity limits, price collars, message throttling, etc.) should also allow for automated blocking or cancellation of unauthorised trades and orders that could jeopardise investment firms' market and credit risk tolerance. *See* RTS 6 art 15.

of trading activity,[610] and 'post-trade' control mechanisms.[611] These systems of internal control primarily serve the purpose of ensuring that trading algorithms:

(i) adhere to predefined limits concerning price collars, order values/volumes, and message rate;[612]

(ii) prevent the emergence of disorderly trading conditions;[613] and

(iii) importantly, that investment firms retain the ability to automatically block or manually cancel trading orders that lack permission to trade or have the potential to jeopardise their credit and market risk exposure.[614]

Although internal control systems can aid human experts in monitoring, identifying, and managing potential instances of market misconduct, there is a concern that investment firms might employ these systems solely to demonstrate regulatory compliance.[615] As previously discussed, in fact, the advent of ML-powered trading has

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610 This function has to be performed by the traders responsible for a particular trading system or strategy and also by the risk management personnel or an independent risk control unit *ad hoc* established for this purpose. This parallel monitoring exercise should enable the risk control function to question the opinion of traders whenever necessary to ensure regulatory compliance. In addition, investment firms should ensure, *inter alia*, that NCAs and trading venues have continuous access to real-time monitoring staff in order to facilitate oversight and regulatory enforcement. *See* RTS 6 art 16.

611 'Post-trade' controls are primarily concerned with the ongoing assessment and monitoring of market and credit risks arising from trading. When they are activated, they should allow for actionable insights, such as adjusting or suspending the operation of trading algorithms or systems. Both traders and the risk control function of investment firms are required to perform this task. *See* RTS 6 art 17.

612 RTS 6 art 15(5).

613 *See* RTS 6 art 16(1).

614 RTS 6 art 15(5). These determinations are made internally by investment firms according to their specific risk appetite and tolerance. *See* RTS 6 art 15(4).

615 *See, e.g.*, Alan Mangelsdorf, 'The EU Market Abuse Directive: Understanding the Implications' (2005) 6(2) Journal of Investment Compliance 30, 33-34 <https://doi.org/10.1108/15285810510644875> accessed 17 July 2024.

introduced novel and unprecedented risks of market manipulation.[616] Yet these risks may have already outpaced technological advancements in the area of internal control systems.[617]

- *Automated surveillance systems*

To effectively detect and mitigate potential risks of market manipulation, investment firms are obligated to monitor all trading activity conducted under their trading code using 'automated surveillance systems'.[618] By generating alerts, reports, and other fundamental material to internally investigate any suspicious activity on a quasi-real-time basis, trading monitoring tools can help investment firms detect suspicious instances of market manipulation.[619] However, it is crucial to consistently update these systems to align with the evolving regulatory and market dynamics, ensuring their adaptability and effectiveness in light of modifications to regulatory obligations, trading strategies, and market functioning.[620]

Automated surveillance systems should provide investment firms with the ability to review trading activity in a granular manner, offering actionable insights by enabling the documentation and analysis of order and transaction data *ex-post* within a low-latency trading environment.[621] In addition, the staff responsible for market surveillance must be equipped to promptly report any suspicious trading activity to the

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616 *See* Chapter 3 (for market manipulation) and Chapter 4 (for algorithmic collusion).

617 *See* Senior Supervisors Group, *Algorithmic Trading Briefing Note* (April 2015) <https://www.newyorkfed.org/medialibrary/media/newsevents/news/banking/2015/SSG-algorithmic-trading-2015.pdf> accessed 17 July 2024.

618 *See* RTS 6 art 13(3). Whenever an investment firm grants other algorithmic market participants access to the market through DEA arrangements, it is subject to the fulfilment of some 'mediated' responsibilities (*see* Articles 19 to 23 of RTS 6), which are intended to prevent the circumvention of regulatory requirements by DEA users.

619 RTS 6 art 13(2).

620 RTS 6 art 13(5).

621 RTS 6 art 13(7).

compliance division. Based on this information, the compliance staff should be empowered to take appropriate actions, which may include reporting to the trading venue or submitting a STOR to NCAs.[622] Furthermore, investment firms must maintain records of their trading activity in financial instruments and submit reports to the respective NCAs to facilitate supervisory monitoring of trading activity.[623]

However, it is worth noting that surveillance systems can be costly, both in terms of in-house development and acquisition from third parties. As a result, firms may not always have the appropriate incentives to invest adequately in these systems.[624] In particular, given that advancements in AI trading have potentially outpaced progress in surveillance technology, firms employing increasingly capable and autonomous ML-powered algorithmic trading systems should prioritise the enhancement of their control systems accordingly.

B. Intermediate 'watchdogs': i.e. trading venues

As intermediate watchdogs, trading venues[625] assume an essential role in supporting market conduct supervision.[626] In their contribution to market integrity, market operators undertake the responsibility of verifying compliance with regulatory obligations imposed by MiFID II and ensure that algorithmic traders on their platforms

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622 RTS 6 art 13(8).

623 *See* MiFID II art 16(6). This framework is further specified by Articles 25-26 of MiFIR. *See* Christian Schmies and Alexander Sajnovits, 'Data Reporting: Market Structures and Regulatory Framework' (2020) European Banking Institute Working Paper Series 2020 – no. 76, 21-22 <https://ssrn.com/abstract=3726054> accessed 17 July 2024.

624 *See, e.g.*, Ross P Buckley and others, 'Regulating Artificial Intelligence in Finance: Putting the Human in the Loop' (2021) 43(1) Sydney Law Review 42, 75-76 <https://www.sydney.edu.au/content/dam/corporate/documents/sydney-law-school/research/publications/slrv43n1mar2021buckleyetaladvance.pdf> accessed 17 July 2024.

625 With the term 'trading venues', this dissertation generally refers to all regulated industry players providing for some sort of electronic trading facility (i.e., 'regulated markets', 'multilateral trading facilities' and 'organised trading facilities'). This terminology follows the EU legal definition. *See* MiFID II art 4(24).

626 *But see, e.g.*, Yadav (n 78).

refrain from engaging in prohibited practices. These practices encompass actions that contravene trading venues' rules, as well as legal prohibitions stipulated under EU MAR/MAD, along with other forms of disruptive conduct.[627]

MiFID II imposes specific organisational and legal requirements on trading venues.[628] For instance, in the event of a suspected case of "significant infringement" of regulatory provisions, trading venues are obligated to promptly inform their home NCA, which, in turn, may share this information with other NCAs and ESMA if necessary for enforcement purposes.[629] Similar to investment firms discussed earlier, the legal framework applicable to trading venues encompasses both *ex-ante* and *ex-post* regulatory safeguards.

i. Ex-ante regulatory requirements

From an *ex-ante* perspective, trading venues contribute to the oversight of algorithmic trading by ensuring adherence to regulatory requirements concerning 'flagging' and 'testing'.

- *Algorithmic flagging*

The act of 'flagging' algorithmic trading activity emerges as a fundamental tool that plays a crucial role in enabling supervisory oversight. It serves as an essential

627 *Cf.* MiFID II art 31 (on market transparency and integrity) and art 54 (on compliance monitoring).

628 For a comprehensive research study addressing similarities and differences between the various legal categories of regulated trading venues, see Danny Busch and Han Gulyas, 'Regulated Markets, Alternative Trading venues & Systemic Internalisers in Europe' (2020) European Banking Institute Working Paper Series 2020 – no. 75 <https://ssrn.com/abstract=3723660> accessed 17 July 2024. Note that a given algorithmic trading firm may also be, at the same time, the provider of a trading platform (e.g., an MTF or OTF). It is often argued in the literature that the parallel exercise of these two activities by the same private organisation may hinder the effectiveness of market conduct supervision. *See, e.g.*, Busch (n 85) 75.

629 *Cf.* MiFID II art 31(2) (for MTF and OTF) and art 54(2) (for "regulated markets") with Commission Delegated Regulation (EU) 2017/565 of 25 April 2016 supplementing Directive 2014/65/EU of the European Parliament and of the Council as regards organisational requirements and operating conditions for investment firms and defined terms for the purposes of that Directive [2017] OJ L 87/1 [hereinafter RTS 7] art 81(2).

prerequisite for identifying specific algorithmic traders and their strategies amidst the vast volume of daily transaction and order book data on regulated trading platforms.[630] Without this regulatory requirement in place, in fact, it would be unfeasible to accurately attribute specific trading orders and transactions to their respective executors.

- *Testing*

The 'testing' requirements imposed on trading venues serve as a primary means of ensuring that algorithmic trading systems operate in a manner that is both operationally and legally compliant. These requirements encompass several minimum obligations pertaining to due diligence for members of trading venues,[631] which include provisions for 'conformance testing' to ensure operational compatibility.[632] Moreover, specific requirements for testing trading algorithms are implemented to prevent disorderly market conditions (i.e. 'behavioural testing').[633]

As these 'testing' requirements largely overlap with those previously discussed in the context of investment firms, they will not be further expounded upon here. However, it is important to note two observations. On the positive side, 'testing' plays a significant role in ensuring system interoperability, business continuity, and resiliency, as well as the adequacy of emergency safety measures in the face of potential malfunctions (e.g., by rejecting orders). Thus, 'conformance testing' aids in mitigating risks associated with algorithm-driven markets, not only in terms of preventing market

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630 *See* MiFID II art 48(10) and MiFIR art 25(2) and (3). For an assessment of the role of algorithmic 'flagging' in financial trading in supporting the knowledge creation of financial regulators, see Nathan Coombs, 'What Is an Algorithm? Financial Regulation in the Era of High-Frequency Trading' (2016) 45(2) Economy and Society 278 <https://doi.org/10.1080/03085147.2016.1213977> accessed 17 July 2024.

631 *See* RTS 7 art 7.

632 *See* RTS 7 art 9.

633 *See* RTS 7 art 10. Since these requirements partly overlap with those mentioned above for investment firms, we do not address them specifically here.

abuse but also in terms of potential systemic impacts. On the negative side instead, there are concerns that current testing regimes may not adequately address the technical specificities and risks associated with specific ML methods (e.g., DRL). To be allowed on trading venues, algorithmic trading systems must meet regulatory requirements. Thus, when found operating on trading venues, an algorithmic trading system is presumed to adhere to these requirements. However, the application of ML methods that are capable of self-learning and often opaque in nature may challenge the validity of existing regulatory frameworks, especially with regard to the testing and auditing of algorithms. Therefore, given the sophistication of algorithmic trading technology, some regulatory gaps seem likely to emerge.

ii. Ex-post regulatory requirements

From an *ex-post* perspective, trading venues are required to establish systems and processes to manage trading orders, ensuring operational resiliency in the face of potential disruptions. They are also required to have specific market intervention arrangements, such as the implementation of 'circuit breaker'[634], to counteract disorderly trading conditions.[635] In addition, in an effort to combat risks associated with algorithmic market manipulation, trading venues are tasked with monitoring trading activity on their platforms and submitting STORs to NCAs.[636] As also these requirements largely mirror those mentioned earlier for investment firms, we will not delve into further detail on them here.

As part of their role in facilitating supervisory oversight, trading venues bear the responsibility of submitting data pertaining to trading activity through their order

634 *See* MiFID II art 48(5).

635 For more details on the whole set of arrangements that trading venues must put in place to prevent disorderly trading condition, see RTS 7 art 18. For a critical account on the role of 'circuit to mitigate risks arising from algorithmic trading activity, see Kern and Loiacono (n 90).

636 Pursuant to Article 16 of MAR, all types of trading venues are required to establish and maintain effective arrangements, systems, and procedures to prevent and detect market manipulation.

books to interested NCAs upon request. In addition, they may also be required to grant NCAs direct access to order book data for the purpose of conducting market surveillance or other enforcement tasks.[637] However, as acknowledged by the ESMA in its MAR review report dated 23 September 2020, the current EU reporting framework for trading activity is not fully conducive to the implementation of cross-market order book surveillance.[638] Unlike 'transaction data', which benefits from full harmonisation in terms of reporting format and submission modalities across the EU,[639] there is a lack of a common technical template or message protocol that trading venues can utilise to transmit 'order book data' to NCAs. As such, the only available options for NCAs to obtain 'order book data' from trading venues are limited to:

(i) *ad hoc* requests for investigating specific cases; and

(ii) broader requests for periodic reporting.[640]

Moreover, although NCAs are able to exchange 'order book data' as part of their cooperative efforts,[641] ESMA also maintains that greater standardisation in messaging formats and data validation techniques would represent a concrete stride towards more efficient cross-market supervision.[642] However, is it worth noting that reporting obligations extend beyond these measures. Trading venues are also required to submit reports on transactions involving financial instruments traded on their platforms in two instances:

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637 MiFID II art 48(11).

638 ESMA (n 309) 128-134.

639 *See* MiFIR art 26(9)(a).

640 *See* MAR art 23 and MiFIR art 25(2).

641 *See* MAR art 25.

642 *Cf.* ESMA (n 309) 132–134.

(i) when such transactions are executed by firms not subject to MiFIR;[643] or

(ii) when they pertain to reference data for individual financial instruments.[644]

It is noteworthy that the availability and equitable accessibility of market data, encompassing both pre-trade and post-trade information, serves as a cornerstone for enhancing the overarching transparency of capital markets and trading activities. On the one hand, enhanced transparency generally benefits investors, enabling them to make well-informed investment decisions. On the other hand, this information is instrumental in facilitating effective market conduct supervision in algorithm-driven markets, thereby promoting integrity and trust in the financial ecosystem.[645]

5.4 The Supervision of Algorithmic Trading Market Conduct

The effective enforcement of market conduct rules is inherently intertwined with the strategy and quality of supervision.[646] Hence, when financial supervisors can effectively oversee markets and identify suspicious trading activities, this bolsters the enforcement of market conduct rules by facilitating the investigation and prosecution of cases of market manipulation.

Within the analytical framework delineated in this chapter, EU market conduct supervisors serve as the 'last line of defence' against algorithmic market manipulation.[647] Nevertheless, as EU capital markets become increasingly fragmented

643 MiFIR art 26(5).

644 MiFIR art 26(1).

645 *See, e.g.*, Austin (n 80); Schmies and Sajnovits (n 623).

646 Ana Carvajal and Jennifer E Elliott, 'The Challenges of Enforcement in Securities Markets: Mission Impossible?' (2009) IMF Working Paper No. 09/18, 4-5 <https://www.imf.org/external/pubs/ft/wp/2009/wp09168.pdf> accessed 17 July 2024.

647 In an enforcement context, the role of the judiciary should also be mentioned. However, since our focus is on issues of regulatory compliance and supervision of market conduct rules, this other category of enforcers is not discussed in this chapter.

and trading assumes a more cross-border nature, the structure of financial supervision in the EU remains somewhat decentralised, organised along national boundaries. As discussed in Chapter 7 in more details, this supervisory architecture may ultimately impair effective supervision of market conduct rules across EU capital markets.

In each Member State, an NCA—generally the same authority entrusted with the regulation and supervision of national capital markets—is responsible for overseeing compliance with market conduct rules.[648] Within their respective jurisdictions, NCAs possess substantial supervisory and law enforcement powers.[649] At the supranational level, the ESMA primarily assumes a coordinating role among NCAs. For example, ESMA is tasked with promoting regulatory technical standards to harmonise the workflow of NCAs and foster convergence in supervisory practices.[650]

In the fight against algorithmic market manipulation, NCAs have two main instruments at their disposal:

(i) the 'acquisition of information' from regulated entities, facilitated, for instance, through various disclosure requirements, trading data reporting, and STORs; and

(ii) 'direct market surveillance', via trade surveillance software, which is somewhat contingent upon the availability and quality of trading data submitted by regulated entities.

648 *See* MAR art 22.

649 *See* MAR art 23 and MiFIR art 24.

650 *See* Regulation (EU) No 1095/2010 of the European Parliament and of the Council of 24 November 2010 establishing a European Supervisory Authority (European Securities and Markets Authority), OJ L 331/84 [hereinafter ESMA Regulation] art 10 (on 'regulatory technical standards') and art 29 (on 'common supervisory culture').

To shed more light on the tools available to financial supervisors, below we elaborate on the EU frameworks concerning (A) the 'information acquisition' and (B) 'direct market surveillance'.

A. Acquisition of information

NCAs possess considerable powers to access information regarding the nature of algorithmic trading systems and strategies employed by investment firms, as stipulated under Article 17(2) MiFID II. The acquisition of information is critical for financial supervisors as it enables them to gain insights into the presence and characteristics of algorithmic trading within their domestic markets. Indeed, this knowledge is a prerequisite for the effective conduct of market surveillance. NCAs also enjoy additional powers to access information concerning algorithmic trading activities, including the ability to receive or request data from market participants under different circumstances.

One of the most significant powers at the disposal of NCAs is the authority to access and request data from both natural and legal persons, albeit subject to a reasonable suspicion that such documents are relevant for investigating cases of market manipulation.[651] More generally, market participants bear certain legal obligations to report trading data. As previously discussed, investment firms, and to some extent, trading venues, are required to maintain transaction records for financial instruments and submit reports to competent authorities. Additionally, under MAR, regulated entities have to submit STORs to NCAs. This regulatory duty can be viewed as an instrumental measure intended to assist financial supervisors in the detection and investigation of instances of market manipulation.

[651] This power, however, needs to be exercised without prejudice to Member States' national law requiring prior authorisation from the judicial authority. *See* MAR art 23(2)(e) and sub-para 2.

B. Direct market surveillance

While there are notable variations in supervisory practices among Member States, all engage to some extent in 'direct market surveillance'. In certain jurisdictions, financial supervisors may be less actively involved in directly monitoring trading activity and instead rely more extensively on market surveillance activities conducted by trading venues. Conversely, other NCAs adopt a more proactive approach, intensively conducting 'direct market surveillance'. This approach allows NCAs to obtain a more comprehensive and detailed perspective on trading activity within and across their national markets.[652]

The effectiveness of market surveillance is closely tied to the availability of technological tools and the expertise of supervisors in analysing trading activity. It also necessarily depends on easy and reliable access to high-quality trading data, including both 'order book' and 'transaction' data). However, as previously mentioned, the EU framework for trading data reporting falls short of ensuring effective market surveillance, particularly concerning order-based forms of manipulation such as 'spoofing'.

Moreover, despite being contemplated by EU legislation, there is currently no EU-wide market surveillance mechanism in place.[653] Given the significant fragmentation of EU capital markets, cross-jurisdiction collaboration among NCAs is crucial for effective supervision and law enforcement against manipulation that occurs across markets and borders. In effect, each NCA has a general duty to cooperate with other NCAs and the ESMA. In the spirit of cooperation, NCAs must exchange information promptly and collaborate on investigative and supervisory activities.[654] However, it is

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652 *See, e.g.*, Austin (n 80) 270-272, discussing the case of German Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin).

653 *Cf.* MAR art 38; *see also* footnote n. 638.

654 *See* MAR art 25(1).

important to note that information exchange arrangements do not facilitate real-time communication. This limitation can, in turn, substantially hinder the effective cross-border enforcement of MAR/MAD.

For the sake of completeness, it should be noted that NCAs may request assistance from their counterparts in other Member States for on-site inspections or other investigative activities. ESMA can also play a coordinating role in supervisory actions among NCAs when requested.[655] It should be emphasised that the same level of cooperation between authorities is expected when NCAs interact with ESMA.[656] Notably, one of the roles of ESMA is to assess the readiness of NCAs in fighting market manipulation, as well as evaluating their effectiveness and the level of convergence in their supervisory practices.[657]

5.5 Conclusion

Within the scope of comprehending the additional risks AI trading introduces to market integrity, this chapter explored the EU's legal framework governing algorithmic market manipulation and the governance of algorithmic trading technology.

The EU's MAR/MAD regime notably proscribes market conducts that undermine the fair and orderly functioning of markets. These rules aim to safeguard market integrity by curtailing the occurrences of market abuse. The ever-changing technological landscape in finance prompted these regulations to accommodate emerging forms of algorithmic market manipulation. Notably, violations can result in administrative and criminal liability for entities and individuals employing algorithmic trading. However, the deployment of AI trading, mainly when powered by ML methods, poses substantial challenges to regulatory bodies. The EU's anti-

655 MAR art 25(6).

656 *See* MAR artt 24 and 25(1).

657 ESMA Regulation art 30.

manipulation law requires—more or less explicitly—enforcement authorities to prove manipulators' *scienter* (i.e., 'intent' or other relevant mental states) with documented evidence. These requirements constrain the effective application of established liability rules for market manipulation in AI-involved scenarios. As will be examined in Chapter 6, these limitations are primarily due to the techno-methodical aspects of specific AI applications. Most notably, due to their increasingly autonomous and often opaque nature, ML-based systems open up unprecedented scenarios where AI autonomously manipulates markets without specific human intent. These scenarios challenge the design of an effective regulatory framework for market conduct, potentially creating a quasi-lawless market environment for AI trading.

Moreover, the integration of ML methods into algorithmic trading raises uncertainties about the adequacy of existing regulatory requirements, as outlined in MiFID II, for the governance of algorithmic trading. This chapter has examined the 'three lines of defence' against the possible adverse effects of negligent and malicious use of trading technology. However, ML trading challenges both the effectiveness of market conduct supervision and the technology governance frameworks applicable to investment firms deploying AI trading. On the one hand, as explored in Chapter 7, the sophistication of ML-based trading strategies, enabling enhanced strategy optimisation and potential market ubiquity, may hinder the ability of EU market conduct supervisors to police trading activity effectively. On the other hand, as addressed in Chapter 8, MiFID II/MiFIR provisions, while addressing technology governance aspects at various institutional levels, may inadequately account for the additional risks associated with AI trading due to the techno-methodical specificities of ML-based applications.

6. LIABILITY RULES AND ENFORCEMENT OF THE PROHIBITION OF MARKET MANIPULATION: ADDRESSING EMERGING CHALLENGES

Rapid technological developments in capital markets, especially those related to ML, require financial regulators to maintain a vigilant stance to responsibly fulfil their institutional mandates, including promoting market integrity. By consistently scrutinising real-world evidence, regulators can gain the knowledge they need to make well-informed decisions. These can include updating regulatory frameworks in light of the additional risks introduced by innovative technologies in the algorithmic trading domain.

As also noted in the previous chapter, one of the main catalysts for the recent reform of EU capital markets law—encompassing the MAR/MAD and MiFID II/MiFIR—was the need to address risks arising from advances in algorithmic trading technology.[658] This reform came in the wake of the first glaring cases of market failure in US capital markets caused by malfunctioning trading algorithms.[659] By contrast, so far, algorithmic trading has not been associated with any significant disruptive events in EU capital markets.[660] Despite the absence of any striking market failures, the relentless and rapid progress in AI trading technology is bound, by and by, to reveal an increasing number of limitations in the current EU market manipulation enforcement regime. In exposing these growing regulatory gaps and with a view at initiating a discussion on how to fill them, this chapter is organised as follows.

658 *See* MiFID II recitals (62) and (63).

659 *See* footnote n. 520 and accompanying text.

660 *Cf*. ESMA (n 129).

First, we present the main technical features of ML-based systems that raise questions about the effective establishment and attribution of liability for misconduct and damages by AI trading (Chapter 6.1). Subsequently, we elucidate how these technical specificities of ML can actually undermine traditional concepts of liability such as ‘causation’, ‘foreseeability’, ’negligence’, and ‘intent’ (Chapter 6.2). Since these concepts of liability also underpin the EU market abuse enforcement regime, we then explore how they may fail to safely be applied in the context of market manipulation involving AI trading (Chapter 6.3). After this general assessment, we introduce the so-called ‘Deterrence Theory’, as derived from the field of Law and Economics, which will serve as a normative framework to address in more depth the issues of liability and deterrence raised by AI trading (Chapter 6.4). Based on the insights provided by models of Deterrence Theory applied to market manipulation by AI, we will discuss some possible policy measures to fill emerging gaps in the current EU enforcement regime. The two proposals focus on reforming the definition of the prohibition of market manipulation into more objective and measurable terms, as well as a new multi-level liability regime at the European level (Chapter 6.5). Eventually, we close the chapter with a summary of the main findings and some concluding remarks (Chapter 6.6).

6.1 AI Techno-Methodical Specificities and Liability Issues

Whenever AI trading is involved in market manipulation actions, several legal challenges regarding liability arise. In particular, there are fundamental issues surrounding the establishment and attribution of liability for AI misconduct and related harm. These issues are closely related to the technical specificities of ML-based trading. Building upon the discussion in Chapter 2.5, in this section we propose a taxonomy of seven main techno-methodical specificities in ML that become cause for concern for liability.

A. Automation and autonomy

Since its first emergence, algorithmic trading has been characterised by increasing levels of automation and autonomy. With the sophistication of trading practices and tools, the active involvement of human experts has become increasingly limited throughout the trading cycle. The integration of ML into algorithmic trading now confers an even greater level of autonomy, to the point that truly autonomous AI trading systems may soon become a reality.[661] But as trading system operations enjoy greater autonomy, this leads to a host of complex liability issues for market accidents, misconducts, and associated harm.[662]

From both conceptual and legal perspectives, the greater autonomy introduced by ML can pose significance challenges when it comes to ensuring human accountability and assigning liability. Specifically, traditional legal concepts of liability like 'causation', 'foreseeability/negligence', and 'intent' may find no safe application in dealing with ML. Unlike deterministic AI systems which operations rely on explicit programming by human experts, ML-based systems develop knowledge through learning from empirical data and, in certain cases, can develop autonomously.[663]

Because of ML self-learning capabilities, attributing liability to specific individuals can become impracticable as the intricate nature of the algorithmic decision-making renders it challenging to trace back human responsibility.[664] Further complicating the matter, enforcement bodies typically find themselves confronted with a long—even open-ended—list of individuals potentially involved in the AI production

[661] *See* discussion in Chapters 2.4-2.5.

[662] *Cf.* footnote n. 76 and discussion in Chapters 3 and 4.

[663] *See* discussion in Chapters 2.3-2.4, 3.3, and 4.4.

[664] *E.g.*, Teresa Rodríguez de las Heras Ballell, 'Legal Challenges of Artificial Intelligence: Modelling the Disruptive Features of Emerging Technologies and Assessing their Possible Legal Impact' (2019) 24(2) Uniform Law Review 302, 308-309 <https://doi.org/10.1093/ulr/unz018> accessed 17 July 2024.

line or AI lifecycle. This aspect complicates effective enforcement further, as the onus of liability is diffused among numerous individuals, which to various extent may have contribution in it.[665] Lastly, the self-learning nature of ML methods introduces an additional hurdle, as potentially responsible individuals may remain unaware or unable to anticipate the system's behaviour.[666]

B. Complexity

The challenge of dealing with increased technical complexity is a well-recognised issue within ICT systems and infrastructures.[667] In contemporary algorithmic trading systems, complexity manifests in various dimensions that warrant particular attention.

First, complexity relates to inherently complex technical design and sophisticated operational functioning of AI systems. Second, complexity refers to the fact that ML-powered trading systems incorporate complex architectures, components, and methods. These AI systems can indeed be seen as complex ecosystems of algorithms, in which multiple software systems and applications interact through intricate networks of hardware components to achieve pre-defined business objectives.[668] Third, the engineering of advanced AI trading systems poses techno-methodical challenges that can only be addressed through the combination of a vast range of human expertise spanning from diverse scientific fields—including, for instance, Mathematics, Data Science, Computer Programming, Financial Theory, and

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665 *See, e.g.*, Ryan Abbott and Alex Sarch, 'Punishing Artificial Intelligence: Legal Fiction or Science Fiction' (2019) 53(1) University of California Davis Law Review 323, 334-337 <https://lawreview.law.ucdavis.edu/sites/g/files/dgvnsk15026/files/media/documents/53-1_Abbott_Sarch.pdf> accessed 17 July 2024, arguing that in some cases it is impracticable to trace AI misconduct back to specific human actors or there may not even be any person responsible; *see also* Jerrold TH Soh, 'Legal Dispositionism and Artificially-Intelligent Attributions' (2023) Legal Studies 1, 18-19 <https://doi.org/10.1017/lst.2022.52> accessed 17 July 2024.

666 *See, e.g.*, discussion in Chapter 2.4.B.

667 *E.g.*, Martin Ebers, 'Regulating AI and Robotics: Ethical and Legal Challenges' in Martin Ebers and Susana Navas (eds), *Algorithms and Law* (Cambridge University Press 2020) 44 <https://doi.org/10.1017/9781108347846.003> accessed 17 July 2024.

668 *See, e.g.*, Koshiyama, Firoozye, and Treleaven (n 165); Rodríguez de las Heras Ballell (n 664) 308.

Capital Markets Law and Regulation, among others.[669] As a consequence, recruiting a team of experts from disparate backgrounds becomes imperative to harness the collective skills required for designing, developing, assembling, training, implementing, deploying, using, and maintaining cutting-edge trading systems.

As the complexity of an AI trading system increases, so does the challenge of controlling and predicting its operation. This complexity poses the risks of unexpected behaviour and operational failures, even when users exercise due care. Overall, the challenges brought about complexity in AI systems can give raise to significant ethical and legal issues concerning human accountability and liability, especially in instances where harm is caused to third parties.

C. Correlation vs. causation

ML methods are data-driven approaches to knowledge discovery, which aim at identifying correlations and patterns from empirical data.[670] Unlike deterministic AI systems that investigates causal relationships between measurements of features, ML-based ones infer statistical patterns and correlations among features from input data.[671] If training data are not good enough, predictions derived from ML may exhibit limited

669 *Cf.* Julius Pfrommer, Thomas Usländer, and Jürgen Beyerer, 'KI-Engineering – AI Systems Engineering: Systematic Development of AI as Part of Systems that Master Complex Tasks' (2022) 70(9) Automatisierungstechnik 756 <https://doi.org/10.1515/auto-2022-0076> accessed 17 July 2024, discussing the emerging discipline of AI System Engineering that deal with the challenges inherent to creating advanced AI systems that leverage ML methods within their various sub-systems and components.

670 *See, e.g.*, Xiaoling Shu and Yiwan Ye, 'Knowledge Discovery: Methods from Data Mining and Machine Learning' (2023) 110 Social Science Research, Article 102817 <https://doi.org/10.1016/j.ssresearch.2022.102817> accessed 17 July 2024.

671 *E.g.*, Buchanan (n 151) 19, stating that "*the key difference between ML and conventional econometrics analysis is its larger focus on prediction compared to summarization and causal inference*"; Daniel Hoang and Kevin Wiegratz, 'Machine Learning Methods in Finance: Recent Applications and Prospects' (2022) European Financial Management 1 <https://doi.org/10.1111/eufm.12408> accessed 17 July 2024, stating that "*[i]nstead of providing insights into the relationships between economic variables, ML tends to serve as a method for prediction or for data structure inference*".

performance (i.e. the so-called 'garbage-in-garbage-out' principle).[672] When this is the case, ML applications can result in under- or over-fitting when confronted with the statistical properties of real-world phenomena, particularly in highly dynamic and noisy environments such as capital markets.[673]

Despite the many benefits offered by ML methods, uncritical reliance on them without considering aspects of causality raises concerns about the reliability of the system's outcomes. Such unconscious applications of ML can thus result in unintended or biased outcomes, highlighting the need for cautious and informed adoption.[674] Now, it should be noted that the field of Financial Econometrics has traditionally been based on correlation analysis of asset prices to inform financial decision-making under conditions of uncertainty.[675]

The integration of ML methods in financial forecasting and analysis carries significant implications for financial theory and practice. On the positive side, ML has the potential to advance our understanding of capital markets and their functioning.[676] Conversely, implementing these methods without a robust theoretical foundation,

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[672] *See, e.g.*, Anjanette H Raymond, Emma Arrington Stone Young, and Scott J Schackelford, 'Building A Better HAL 9000: Algorithms, The Market, and the Need to Prevent the Engraining of Bias' (2018) 15(3) Northwestern Journal of Technology and Intellectual Property 215, 222 and footnote n. 31 therein <https://scholarlycommons.law.northwestern.edu/njtip/vol15/iss3/2> accessed 17 July 2024.

[673] *See* Lopez de Prado (n 161) 101.

[674] *E.g.*, Ebers (n 667) 45.

[675] *See, e.g.*, footnote n. 671; *see also* Markus Schuller and Andreas Haberl, 'Causality Techniques in Investment Management: Five Key Findings' (*CFA Institute Blog*, 16 March 2022) <https://blogs.cfainstitute.org/investor/2022/03/16/causality-techniques-in-investment-management-five-key-findings> accessed 17 July 2024.

[676] *See, e.g.*, Stefan Nagel, *Machine Learning in Asset Pricing* (Princeton University Press 2021) 4-7, arguing that the application of ML methods in asset pricing can foster advances in the theoretical modelling of financial markets.

with respect to mathematical methods and data, can lead to unreliable application introducing new sources of model risk in finance.[677]

D. Data dependency

ML-based systems learn from large amounts of data processed by complex algorithms, potentially making it challenging for human experts to comprehend and explain their inner working.[678] Moreover, the reliability and validity of a system's outcomes can be compromised by various factors. The latter include, for instance, biases embedded in the data itself (e.g., stemming from statistically insignificant training data) or biases introduces by human actors (e.g., arising from the basic assumptions adopted by the model to learn the target function and generalise from the training data).[679] Thus, it is crucial to place a strong emphasis on data governance[680] measures to mitigate the risks associated with biased or flawed data that may result in harmful outcomes.[681]

In scenarios where a given AI trading system's output leads to misconduct and harm to markets, the data dependency feature of ML exacerbates the difficulty of

677 *See, e.g.*, Iqbal H Sarker, 'Machine Learning: Algorithms, Real-World applications and Research Directions' (2021) 2 SN Computer Science, Article 160, 17 <https://doi.org/10.1007/s42979-021-00592-x> accessed 17 July 2024: *see also* Bakkar and others (n 239) 23.

678 *E.g.*, Rodríguez de las Heras Ballell (n 664) 309 and footnote n. 23 therein.

679 *See* discussion in Chapter 2.5.A.

680 In the field of ML, the term 'data governance' refers to the set of processes, policies, and measures that ensure the effective management, quality, security, and use of data within an organisation that underpin the trustworthy application of AI systems. *See, e.g.*, Marijn Janssen and others, 'Data Governance: Organizing data for Trustworthy Artificial Intelligence' (2020) 37(3) Government Information Quarterly, Article 101493 <https://doi.org/10.1016/j.giq.2020.101493> accessed 17 July 2024.

681 *See, e.g.*, Li Cai and Yangyong Zhu, 'The Challenges of Data Quality and Data Quality Assessment in the Big Data Era' (2015) 14 Data Science 2 <https://doi.org/10.5334/dsj-2015-002> accessed 17 July 2024; Kristian Bondo Hansen and Christian Borch, 'Alternative Data and Sentiment Analysis: Prospecting Non-Standard Data in Machine Learning-Driven Finance' (2022) 9(1) Big Data & Society 1, 8 <https://doi.org/10.1177/20539517211070> accessed 17 July 2024, discussing issues of data governance in dealing with alternative data and Big Data.

establishing causation, which is a prerequisite to ensure smooth and effective enforcement.

E. Interconnectedness

Another main distinguishing feature of electronic trading is the integration of trading algorithms within highly interconnected market environments. In these dynamic and complex marketplaces, increasingly sophisticated algorithms observe and interact with each other in competition, performing operations even at the speed of light. Algorithmic interconnectedness, however, also brings the potential for market disruptions to spread rapidly through contagion effects. A prime example of this occurred in August 2012 when the US stock markets experienced a notorious trading algorithm debacle at Knight Capital, wherein a single rogue algorithm triggered non-linear effects on the broader market, resulting in significant losses and disruptions.[682]

As this example shows, the interconnected nature of the operation of trading systems poses challenges when it comes to attributing liability for harm to markets. The intricate complexity of these systems, combined with the rapidity with which operations are performed, makes it difficult to identify the precise cause of a particular adverse event. Likewise, ascertaining the specific actor(s) responsible for the resulting damage becomes a daunting task. Lastly, the interconnectedness of these systems may also give rise to widespread liability among competing market participants, where multiple actors are jointly responsible for the harm caused. Establishing precisely the participation in liability of individual actors can be an even more complicated exercise given the potentially large number of actors involved and the difficulty in determining their precise contribution.[683]

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[682] *See* discussion in Chapter 3.2.B and footnote n. 321.

[683] *See, e.g.*, Yadav (n 65); Fletcher (n 75); Rodríguez de las Heras Ballell (n 664); Barr and others (n 344).

F. Opacity

Among the myriad concerns surrounding the use of ML in finance, the issue of opacity—commonly referred to as the black box problem—stands out as particularly critical and subject to extensive policy analysis and debate.[684] While ML can help optimise a number of tasks in financial trading, the resulting market behaviour can be highly opaque, rendering it difficult for human experts to understand and explain the rationale pursued by their algorithms to achieve a specific outcome.[685]

The opacity arising in AI trading can stem from various practical factors.[686] At its most fundamental level, opacity can be a deliberate design choice by private organisations seeking to safeguard the specific details of their algorithmic systems and strategies for competitive advantage.[687] On other occasions, opacity may be reflection of the limited understanding of ML among its human stakeholders. In such cases, opacity arises from a lack of specialised skills within a given organisation necessary for the design, the development, and/or use of specific AI trading systems.[688] Lastly, opacity may be an unavoidable consequence of employing complex and sophisticated AI systems that leverage specific ML methods (e.g., based on DL).[689] Regardless of the exact cause, a lack of transparency and explainability in AI systems raises significant ethical, legal, and regulatory concerns, particularly when such systems are deployed in critical application domain like financial trading.[690]

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684 *See, e.g.*, Rodríguez de las Heras Ballell (n 664) 309-310.

685 *See* discussion in Chapter 2.5.B.

686 *See* Burrell (n 265).

687 Ibid 3.

688 Ibid 4.

689 Ibid 4-5.

690 As unfortunate historical examples show, capital markets trading is a critical domain for our global society. But this seems an aspect that is too often ignored by policymakers. *See, e.g.*, footnote n. 260.

G. Vulnerability

AI trading systems are complex ecosystems of algorithms, which operate through a combination of software and hardware components. These algorithms are capable of processing large amounts of data, sometimes operating at high speed.[691] Ensuring the security and integrity of these systems is paramount to guarantee their safe and reliable performance. Moreover, the presence and exploitation of technical vulnerabilities can compromise the proper functioning of AI systems, potentially leading to undesirable behaviour and exposing organisations to the risk of financial loss. In particular, AI-powered trading systems remain vulnerable to a range of threats, including cyber-attacks, software glitches, and other sources of malfunction.[692] A prominent example of cyber-vulnerability emerges in the form of 'data poisoning' attacks. The latter entail deliberate intrusions by third parties with the aim to corrupt or manipulate the AI input data by introducing false or misleading information. Such attacks can significantly impact the performance and reliability of AI systems, distorting their learning process and leading to compromised decision-making.[693]

In cases of market incidents involving systems hacked by third parties, liability issues may arise, as it is often difficult to ascertain the true cause of a system malfunction. Determining the identity of those responsible for the negative effects of cyber-attacks or security breaches requires considerable investigative efforts and technical knowledge to shed light on the incident. In particular, in order to ascertain the precise cause of malfunctions or errors, it is not sufficient to examine individual algorithmic systems in isolation, which may be a complex task in any case. An effective assessment of liability rather requires considering AI systems as integral parts of much

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691 *See* discussion in Chapter 2.3.

692 *See, e.g.*, Rodríguez de las Heras Ballell (n 664) 310.

693 *See* Fahri Anıl Yerlikaya and Şerif Bahtiyar, 'Data Poisoning Attacks Against Machine Learning Algorithms' (2022) 208 Expert Systems with Applications, Article 118101 <https://doi.org/10.1016/j.eswa.2022.118101> accessed 17 July 2024.

larger and more complex ICT networks (i.e. the markets and their technological infrastructure) on which they actually operate.[694]

Overall, issues related to the vulnerability of algorithmic trading systems can be addressed through suitable policies and measures on the development, implementation, and maintenance of cybersecurity standards and protocols capable of safeguarding the security and operational integrity of these systems.[695] Although cybersecurity risks cannot be eliminated entirely, companies are required to develop an organisational culture and equip themselves with the necessary resources and tools to mitigate these threats.[696]

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In sum, due to the seven technical specificities of ML discussed above, the effective enforcement of market conduct rules against AI trading may face obstacles. Indeed, even more deterministic AI systems—hence non-ML—can generally complicate enforcement action. However, the delegation of cognitive agency and decision-making to ML-based systems further exacerbate enforcement issues, significantly widening the 'accountability gaps' that typically arise when algorithmic trading is involved in market manipulation.[697] As we shall see, the most extreme cases

[694] *See* footnotes n. 232-239 and accompanying text as well as discussion in Chapter 4.1.

[695] It should be noted that among the many and sometimes stringent organisational and legal requirements that EU financial regulations impose on investment firms using algorithmic trading, cybersecurity aspects are not regulated in such an explicit and detailed manner. *See, e.g.*, Anton N Didenko, 'Cybersecurity Regulation in the Financial Sector: Prospects of Legal Harmonization in the European Union and Beyond' (2020) 25(1) Uniform Law Review 125, 160-161 <https://doi.org/10.1093/ulr/unaa006> accessed 17 July 2024.

[696] Not surprisingly, among the latest developments in technology to support cyber resilience, the most innovative companies are making use of AI-powered systems. *See, e.g.*, Zhibo Zhang and others, 'Explainable Artificial Intelligence Applications in Cyber Security: State-of-the-Art in Research' (2022) 10 IEEE Access 93104 <https://doi.org/10.1109/ACCESS.2022.3204051> accessed 17 July 2024, conducting a literature review on XAI applications in cyber security. The authors highlight the critical importance of XAI to create explainable models that allow human users to comprehend, trust, and manage most sophisticated cyber defence systems.

[697] *See* footnote n. 263 and accompanying text.

occur whenever market manipulation is due to the activity of autonomous ML-based trading systems that behave as black boxes.

6.2 General Challenges for Traditional Legal Concepts of Liability

Legal issues related to liability for misconduct and harm caused by AI have been under consideration by EU legislators for some time.[698] At the same time, legal scholars have contributed numerous alternative legal theories to this discourse.[699] However, a

[698] In February 2020, the European Commission published a white paper outlining a range of policy options on how to ensure the trustworthy adoption of AI technologies, while also addressing key issues related to liability for damage caused by these systems. *See* European Commission, 'White Paper: On Artificial Intelligence – A European Approach to Excellence and Trust' (19 February 2020), COM(2020) 65 final [hereinafter Commission's White Paper]. As a more recent development, in September 2022, the same Commission introduced a draft proposal for an AI Liability Directive, designed to address private law issues arising from harm caused by AI systems within the Union. The primary goal of this proposal is to provide a framework to simplify the procedure for filing claims related to damages resulting from the use of AI. It seeks to provide clarity on legal aspects, such as causality and fault linked to AI-induced incidents, in order to ensure that victims who suffer losses caused by AI systems can access compensation and other legal remedies. *See* European Commission, 'Proposal for a Directive of the European Parliament and of the Council on Adapting Non-Contractual Civil Liability Rules to Artificial Intelligence (AI Liability Directive)' (28 September 2022), COM(2022) 496 final.

[699] A growing number of scholarly publications have addressed the liability issues raised by AI. Some of the most influential studies—at least for the purpose of the present research—that are worth mentioning include, for example: Samir Chopra and Laurence F White, *A Legal Theory for Autonomous Artificial Agents* (University of Michigan Press 2011) <https://doi.org/10.3998/mpub.356801> accessed 17 July 2024, which is one of the first books to comprehensively and neatly examine the legal aspects and issues related to artificial agents; David C Vladeck, 'Machines Without Principals: Liability Rules and Artificial Intelligence' (2014) 89(1) Washington Law Review 117 <https://digitalcommons.law.uw.edu/wlr/vol89/iss1/6> accessed 17 July 2024, arguing that legal systems will be seriously put to test by the introduction of autonomous algorithmic systems; Hallevy (n 562), representing one of the first comprehensive studies relating to issues of liability for crime involving AI systems; Ryan Calo, 'Robotics and the Lessons of Cyberlaw' (2015) 103(3) California Law Review 513 <https://digitalcommons.law.uw.edu/faculty-articles/23> accessed 17 July 2024, who consider the exceptional nature of AI, particularly robotics, capable of bringing about systemic changes in law, institutions, and legal research; Amitai Etzioni and Oren Etzioni, 'Keeping AI Legal' (2016) 19(5) Vanderbilt Journal of Entertainment and Technology Law 133 <https://scholarship.law.vanderbilt.edu/jetlaw/vol19/iss1/5> accessed 17 July 2024, addressing both opportunities and risks introduced by AI for legal systems; Ryan Abbott, 'The Reasonable Computer: Disrupting the Paradigm of Tort Liability' (2018) 86(1) George Washington Law Review 1 <https://www.gwlr.org/wp-content/uploads/2018/04/86-Geo.-Wash.-L.-Rev.-1.pdf> accessed 17 July 2024, arguing that as technological advances make it possible to create computer systems that are more secure than humans, the law will have to be based on different legal standards and liability rules tailored to the capabilities and quality of these systems; Bathaee (n 76), examining liability issues for AI-enabled misconduct and harm; Iria Giuffrida, 'Liability for AI Decision-Making: Some Legal and Ethical Considerations' (2019) 88(2) Fordham Law Review 439 <https://ir.lawnet.fordham.edu/flr/vol88/iss2/3> accessed 17 July 2024, addressing both legal implications and liability issues associated with AI adoption; Gerhard Wagner, 'Robot, Inc.:

common observation apparently shared by emerging legal theories is that traditional legal concepts of liability are bound to face a significant challenge in the AI context, especially as algorithmic systems become more autonomous.

Below we analyse the legal implications that AI trading bring in the context of the enforcement of the prohibition of market manipulation. As we will see, the use of ML methods can hinder or even prevent the determination of certain human mental states necessary to attribute liability for market manipulation. To illustrate this point, we examine the inherent problems encountered when traditional legal concepts of liability—such as (A) 'causation', (B) 'foreseeability' and 'negligence', and (C) 'intent'—are applied to the context of misconduct and harm by AI trading.

A. Causation

Delegating cognitive agency and decision-making to AI systems raises concern regarding the application of liability tests based on the concept of 'causation'.[700] Specifically, establishing a causal link between the 'cause'—such as a particular market manipulation strategy—and the 'alleged harm'—such as unfair market conditions and/or financial loss—is a critical element in assessing the extent of legal liability

Personhood for Autonomous Systems' (2019) 88(2) Fordham Law Review 591 <https://ir.lawnet.fordham.edu/flr/vol88/iss2/8> accessed 17 July 2024, who discusses the impact of AI and related technologies on markets, highlighting related liability issues; Karni A Chagal-Feferkorn, 'Am I an Algorithm or a Product? When Product Liability Should Apply to Algorithmic Decision-Making' (2019) 30 Stanford Law & Policy Review 61 <https://law.stanford.edu/wp-content/uploads/2019/05/30.1_2-Chagal-Feferkorn_Final-61-114.pdf> accessed 17 July 2024, who analyses how the delegation of tasks to artificial intelligence systems alters traditional concepts and frameworks of liability; Abbott and Sarch (n 665), who identify the limitations, both practical and conceptual, of traditional criminal law and its instruments in dealing with AI crimes; Jacob Turner, *Robot Rules: Regulating Artificial Intelligence* (Palgrave Macmillan 2019) <https://doi.org/10.1007/978-3-319-96235-1> accessed 17 July 2024, providing an examination of existing legal regimes to address the unique risks associated with AI technology; Thomas C King and others (n 333), conducting an interdisciplinary analysis of the threats associated with AI misconduct and crime; Simon Chesterman, 'Artificial Intelligence and the Limits of Legal Personality' (2020) 69(4) International & Comparative Law Quarterly 819 <https://doi.org/10.1017/S0020589320000366> accessed 17 July 2024, who revies emerging legal theories on AI regulation and cautions about the limits of granting legal personhood to AI.

[700] *E.g.*, Bathaee (n 76) 922.

attributed to an alleged manipulator.[701] However, in cases involving market manipulation by algorithmic systems, the process of identifying the true cause and substantiating the actual damage can generally be an arduous task for affected parties and enforcement bodies alike, even when dealing with deterministic AI systems.[702] This challenge is further amplified when ML-powered systems or strategies are involved, as establishing 'causality' can become practically infeasible due to the above-mentioned technical specificities of these systems.

The intricate design and sophisticated operation of ML-based systems, their increasing autonomy and often opaque nature, coupled with the high interconnectedness within real-market environments, all contribute to several challenges in establishing the required link of 'causality' in cases of market manipulation and harm. Due to ML, AI trading has indeed the potential to disrupt the causal chain between a specific wrongful practice and the resulting financial loss or unfair market conditions experienced by others.

B. Foreseeability and negligence

The application of the legal concepts of 'foreseeability' and 'negligence' in the context of AI trading also presents challenges.[703] According to the legal doctrine of foreseeability, liability assessment for cases of misconduct requires to determine what could reasonably be anticipated by the alleged wrongdoer to avoid harm. This legal doctrine requires law enforcement authorities to establish whether a reasonable person could have foreseen the effects of the alleged misconduct. In affirmative, then, this helps determine whether conduct constitutes an offence.[704] Whenever a misconduct

[701] *See* discussion in Chapter 5.2.

[702] *See* footnote n. 683.

[703] *See, e.g.*, Yadav (n 65) 1076-1081; Bathaee (n 76) 914.

[704] For an introduction to the legal concept of 'foreseeability' from a Law & Economics perspective, see Omri Ben-Shahar, 'Causation and Foreseeability' in Michael Faure (ed), *Tort Law and Economics* (Edward Elgar Publishing 2009) 83-108.

arise from the use of AI systems, however, the key legal question becomes what constitutes outcomes and behaviours that can be reasonably foreseen by human experts, including the designers, developers, users, or controllers of AI. In this context, not only do law enforcement authorities find it difficult to establish causation, but even the same human experts involved in the AI lifecycle may struggle to predict and thus control the ways in which their AI systems may behave and potentially cause harm to markets.

Similarly, the application of the legal concept of 'negligent' as a liability rule can be challenging.[705] Negligence generally refers to a failure to exercise reasonable care to prevent harmful consequences resulting from one's actions or inactions, despite having the capability and responsibility to take appropriate measures of due care.[706] However, AI trading introduces complexities that impede the straightforward application of the concept of negligence to cases of market manipulation. This is mainly due to the increasing autonomy and often opaque nature of AI systems, which make it difficult to determine whether the negligent behaviour of human experts is behind a certain misconduct. For instance, it can be impractical to assess whether a particular AI trading system was poorly designed or whether the misconduct is attributable to other factors. In addition, the increasing sophistication of ML-based trading systems contributes to difficulties in establishing an appropriate standard of care for assessing whether their use was negligent.[707]

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[705] *See, e.g.*, Yadav (n 65) 1077-1082, discussing the difficulties prosecutors generally face in applying fault-based test such as negligence, especially when dealing with HFT strategies.

[706] *See, e.g.*, Richard A Posner, 'A Theory of Negligence' (1972) 1 Journal of Legal Studies 29 <https://www.journals.uchicago.edu/doi/epdf/10.1086/467478> accessed 17 July 2024.

[707] *See, e.g.*, Chris Reed, Elizabeth Kennedy, and Sara Nogueira Silva, 'Responsibility, Autonomy and Accountability: Legal Liability for Machine Learning' (2016) Queen Mary School of Law Legal Studies Research Paper No. 243/2016, 10-12 <https://ssrn.com/abstract=2853462> accessed 17 July 2024.

C. Intent

Misconduct involving AI systems also complicates the assessment of liability under the legal concept of 'intent'.[708] In many jurisdictions, intent is a decisive element in determining liability for misconduct and harm. Essentially, this legal concept refers to deliberate and conscious actions committed with the specific purpose of causing harm or engaging in criminal activities, such as serious market manipulation offences. The burden of proving intent typically falls on enforcement bodies and plaintiffs, who must present sufficient evidence demonstrating that the manipulator acted with the requisite intent in committing an alleged case of market manipulation.[709]

As examined in Chapter 5, while, under EU law, the criminal prosecution of market manipulation requires proof of intent to establish liability, violations of the administrative prohibition under MAR do not necessarily demand proof of intentional conduct to count as an offence. However, even in the latter case, evidence of a relevant mental state, such as negligence, is usually required to effectively differentiate manipulative conduct from legitimate trading activity. In the context of trade-based forms of market manipulation, for instance, it can be particularly challenging to effectively distinguish manipulative trading from legitimate one (e.g., market making strategies), due to their often seemingly innocuous, hence *bona fide*, nature. In the US, indeed, where successful enforcement of the prohibition against market manipulation requires proof with documented evidence of intentional misconduct on the part of the

[708] *See, e.g.*, Hallevy (n 562) 82-101; Yadav (n 65) 1073-1077; Bathaee (n 76) 906-921; Fletcher (n 75) 300-304; Feldman and Stein (n 94) 105-111; Hal Ashton, 'Defining and Identifying the Legal Culpability of Side Effects Using Causal Graphs' in Gabriel Pedroza and others (eds), *SafeAI 2022 – Artificial Intelligence Safety 2022: Proceedings of the Workshop on Artificial Intelligence Safety 2022 (SafeAI 2022) co-located with the Thirty-Sixth AAAI Conference on Artificial Intelligence (AAAI2022)* (CEUR-WS.org 2022) 1-9 <https://discovery.ucl.ac.uk/id/eprint/10146135/1/paper_27.pdf> accessed 17 July 2024.

[709] *See, e.g.*, Jeremy Horder, *Ashworth's Principles of Criminal Law* (9th edn, Oxford University Press 2019) 190.

manipulator, the very legal concept of market manipulation has sparked intense debate in the academic literature and courts.[710]

Besides the broader issues related to the legal treatment of intent in the context of market manipulation, the involvement of AI systems in misconduct introduces additional complications in the assessment of intentional liability. For one thing, it is particularly difficult—if not entirely inappropriate—both conceptually and legally to speak of intentional behaviour on the part of AI systems.[711] Since AI lacks consciousness akin to human consciousness, it cannot act intentionally *per se*. Beyond this latter consideration, however, it is clear that the involvement of AI systems in misconduct makes it hard to ascertain the intent of the individuals potentially involved. As discussed in Chapter 3.2, there are various scenarios in which AI trading can be involved in market manipulation. For instance, AI manipulative tendency may result from explicit programming or training by human experts (Scenario C). But, with the growing capabilities offered by certain ML methods, AI trading systems may also engage in misconduct autonomously while optimising the achievement of a pre-defined business objective (Scenario D). Distinguishing between these two possibilities could be extremely difficult for law enforcement authorities. And in any case, these would still have to weigh the different liability contributions to a long, potentially open-ended, list of individuals involved in the AI production chain, all of whom could be liable in some way for AI misconduct.

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In sum, in light of the technical specificities characterising AI trading that is powered by ML, the effective application of established liability rules for market manipulation may find increasingly hard scope of application. Particularly, traditional

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[710] *See, e.g.*, Fischel and Ross (n 364); Fox, Glosten, and Guan (n 71); Fletcher (n 75); Barr and others (n 344).

[711] *But see* Ashton (n 348), who proposes an analytical framework to assess intentional misconduct by algorithmic agents.

legal concepts of liability—namely, 'causation', 'foreseeability', 'negligence', and 'intent'—underpinning the legal prohibition of market manipulation may prove inadequate to provide a robust conceptual and legal framework to safeguard the effective enforcement of market conduct rules. Consequently, due to ML, certain AI applications in financial trading can easily bypass existing legal framework, thus left operating in a quasi-law-less market environment. In this sense, ML methods introduce an additional layer of complexity to the understanding and control of algorithmic trading systems' behaviour and its collective impact on the fair and orderly functioning of markets. Indeed, discerning whether misconduct involving AI trading is due to as an unintended consequence, inspired by some prior human intent, or result from autonomous decision-making by AI, will be increasingly challenging. As such, the quality, integrity, and ultimately the overall stability of global capital markets may be perilously put at risk.

6.3 Ineffective Deterrence of AI Trading Misconduct

After an examination of liability issues arising in the context of AI trading, we now turn to evaluating their implication for ensuring effective enforcement of EU market conduct rules. As will be argued, despite the primary objective of establishing a robust and homogeneous regulatory framework to fight against market abuse in European capital markets, there are compelling reasons to believe that the current regulatory regime suffers from several weaknesses in achieving credible deterrence and thus effective enforcement.

One of the primary fragilities of the current regime lies in the uncertain nature of the legal prohibitions coupled with their partially inconsistent implementation and enforcement among EU member states.[712] As we shall see, this creates fertile ground for 'regulatory arbitrage' that investment firms using AI trading can exploit to their advantage. Indeed, AI trading can find itself operating in a market environment that

[712] *See* discussion in Chapter 5.2.

lacks clear legal boundaries. This situation places the deterrent effect of the law against algorithmic market manipulation dangerously at risk, particularly when such activities span multiple markets or cross-national borders.

A. Uncertain legal prohibitions

AI trading may pose a threat to market integrity, which stands as a paramount objective of EU financial law. Of particular concern is the capacity of AI to optimise, thanks to ML, both old and new forms of market manipulation, including the emergence of subtle forms of 'tacit' collusion. Indeed, AI-optimised forms of market abuse may fall outside the purview of existing EU anti-manipulation legislation. In particular, users of AI trading may face great incentives to exploit the ambiguities of established legal prohibitions.

As previously discussed, when trying to address market manipulation cases involving AI, a noteworthy problem arises, namely the requirement to establish a culpable mental state in order to consider such conduct as an administrative offence or a criminal act. This is particularly evident in the context of criminal law. Conversely, the application of anti-manipulation law within the framework established by MAR may appear less problematic, at least from a conceptual point of view. But as already noted, the task of distinguishing between actual or attempted manipulation and legitimate trading activity remains challenging even in this context.

To elucidate the intricate nature of the challenges introduced by AI trading, due to ML, in relation to the aforementioned legal concepts, one should keep in mind that a given instance of algorithmic market manipulation may be due to several contingencies.[713] By way of illustration, in the absence of faulty or deliberate human conduct, misconduct by an AI system could be a result of counter-intuitive computational reasoning, the extrapolation of latent patterns through powerful and

[713] *See* discussion in Chapter 3.2.

somewhat inexplainable-to-human DL analytical capabilities, or the exploitation of trading strategies that human traders would not typically conceive.[714] Further complicating the matter , the rapid pace at which algorithmic trading systems operate in the markets, coupled with all possible sort of interactions with diverse agents—both human and algorithmic—within the complex and highly interconnected environment of capital markets, impedes the application of foreseeability as a legal test and the establishment of causation.[715]

Even when law enforcement bodies can identify a specific AI trading system responsible for an alleged case of market manipulation, they confront the arduous task of assessing liability within the organisation using such a system. In principle, multiple individuals could potentially bear some contribution in liability. For instance, responsible persons may include those individuals enjoying organisational authority (e.g., board members such Chief Information Officers or Chief Technology Officers, who decide upon the proliferation and implementation of AI-related projects) and those possessing the expertise required for the creation, development, deployment, use, and maintenance of a given proprietary AI trading system.

In addition, in cases where some AI components or systems are purchased from third-party vendors, financial regulators may need to shed light on the role of these external actors in order to make sure that trading systems are adopted in a way that complies with the law.[716] In fact, users of AI systems may not be fully in control of certain aspects and processes of the AI lifecycle, which raises questions in terms of

[714] *See, e.g.*, Bathaee (n 76) 924; Carrol and others (n 481) 8-9.

[715] *See* discussion in Chapter 6.2.

[716] *Cf.* Gary Gensler and Lily Bailey, 'Deep Learning and Financial Stability' (2020) SSRN preprint 1, 30-31 <https://ssrn.com/abstract=3723132> accessed 17 July 2024; Alexander C Culley, 'Insights into UK Investment Firms' Efforts to Comply with MiFID II RTS 6 That Governs the Conduct of Algorithmic Trading' (2023) 31(5) Journal of Financial Regulation and Compliance 607, 627 <https://doi.org/10.1108/JFRC-12-2022-0144> accessed 17 July 2024, who also propose a novel regulatory regime for qualified third-party providers.

effective contribution in liability for cases of malfunction and market abuse.[717] Given that AI trading systems constitute complex ecosystems of algorithms, comprising numerous software and hardware components, investigations and law enforcement actions may be significantly impeded by the substantial information asymmetry prevailing between AI users (and providers) and law enforcement authorities.

Lastly, it is worth noting that the current EU anti-manipulation law excludes certain financial instruments, such as foreign exchange spot transactions[718] and crypto assets[719], from the ambit of market conduct regulations. This exclusion raises additional concerns, as it disregards the potential contagion effects that certain manipulated instruments can exert on the broader market.

Hence, in what follows we discuss how the divergent implementation of market conduct rules by EU Member States may also hinder the achievement of credible deterrence and thus effective enforcement, giving us additional reasons to better investigate the risks posed by AI trading to market integrity.

B. A (still) too fragmented liability and enforcement regime

As previously discussed, one main cause of enforcement failure stems from the rather fragmented implementation of market conduct rules across EU Member States—a phenomenon commonly referred to as the problem of 'divided interpretation'.[720] This fragmentation can pose substantial challenges to effective enforcement especially due to the cross-asset, cross-market, and cross-border capabilities of certain trading strategies. While AI trading can leverage extensive scope of action and potentially

[717] Although the AI Liability Directive is still under political discussion at the time of writing, it is not yet clear whether and to what extent it will apply to AI-powered algorithmic trading systems.

[718] *See* footnote n. 309 and accompanying text.

[719] *But see* footnote n. 525 and accompanying text.

[720] *See* Chapter 5.2.

operate ubiquitously within European markets, the EU enforcement regime of market conduct rules is organised along national silos. This fragmentation has several implications for effective law enforcement against AI trading.

To begin, the lack of uniform adoption of criminal law measures for serious instances of market manipulation across Member States may result in divergent enforcement outcomes throughout the EU.[721] The uncertain equivalence of administrative and criminal sanctions, in fact, introduces discrepancies in the enforcement capabilities of Member States, to the extent that criminal sanctions replace administrative ones. Specifically, in enforcing the prohibition of market manipulation under criminal law, public enforcers may lack certain legal instruments that the MAR designates as minimum administrative powers for NCAs, such as, for instance, the cooperation regime among NCAs and ESMA as provided by Articles 24 and 25 of MAR.[722]

In connection with the above observation, there is another consideration. When dealing with cases of cross-border market manipulation, the uncertain relationship between administrative and criminal measures, which can be triggered by Member States' supervisory bodies, may lead to uncertain and uneven results among the various authorities involved. Such a possibility may therefore amount to an additional cause for ineffective enforcement of market conduct rules in the EU.[723]

Furthermore, not all Member States incorporate provisions for 'corporate criminal liability' (e.g., in Germany). As a liability rule, 'corporate criminal liability' is a

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721 *See generally* Andrea Perrone, 'EU Market Abuse Regulation: The Puzzle of Enforcement' (2020) European Business Organization Law Review 379 <https://doi.org/10.1007/s40804-019-00171-x> accessed 17 July 2024.

722 *See* ibid 385.

723 *See* Michiel Luchtman and John Vervaele, 'Enforcing the Market Abuse Regime: Towards an Integrated Model of Criminal and Administrative Law Enforcement in the European Union?' (2014) 5(2) New Journal of European Criminal Law 192 <https://doi.org/10.1177/203228441400500205> accessed 17 July 2024.

subject of ongoing debate as a fundamental enforcement tool for achieving credible deterrence. The prospect of threatening investment firms with criminal liability can contribute to deterring misconduct, as it establishes positive incentives for cooperation with enforcement bodies by means, for instance, of monitoring of trading activities and self-reporting of suspicious cases of manipulation.[724]

In sum, the existence of uncertain legal prohibitions and quite fragmented regulatory regimes among Member States, which is partly attributable to national disparities in the treatment of liability rules for market manipulation, raise substantial concerns regarding the ability of the EU framework to ensure credible deterrence thus effective law enforcement against AI trading. When the fragmented implementation of the MAR+MAD regime is compounded by a similarly decentralised interpretation and implementation of MiFID II rules, concerning the governance of algorithmic trading and electronic trading platforms,[725] there are further doubts regarding the effectiveness of the EU approach in safeguarding market integrity. Overall, AI trading may result being left operating in a quasi-lawless market environment. Malicious actors can exploit regulatory arbitrage facilitated by the current EU anti-manipulation law, thereby creating possibilities for 'forum-shopping'. In light the above-identified gaps, in what follows we explore some potential avenues to strengthen the deterrence credibility of the current enforcement regime. As a normative framework of analysis, the present investigation proposes to apply 'Deterrence Theory' as developed by the scientific field of Law and Economics.

[724] *See* Jennifer Arlen and Lewis A Kornhauser, 'Battle for Souls: A Psychological Justification for Corporate and Individual Liability for Organizational Misconduct' (2023) 2023 University of Illinois Law Review 673, 678, 723 and 724 <https://illinoislawreview.org/wp-content/uploads/2023/05/Battle-for-our-Souls.pdf> accessed 17 July 2024.

[725] *See* Karremans and Schoeller (n 78) 40-47.

6.4 The Law and Economics of Deterring Market Manipulation

Most sophisticated practices of market manipulation typically manifest as forms of white-collar crime.[726] These unscrupulous actors employ gimmicks, swindles, and deceptive strategies in order to extract profits that would otherwise be unattainable. Throughout the history of finance, market manipulation has proven to be one of the most intractable financial wrongs for enforcement authorities, given all the inherent difficulties involved in detecting, investigating, and prosecuting such cases.[727] These enforcement challenges are further amplified in the realm of algorithmic market manipulation and become even more complex in the presence of AI agency.

A primary objective of any enforcement regime is to put in place legal prohibitions, liability rules, and enforcement mechanisms able to effectively deter would-be manipulators.[728] In this section, we aim to unlock valuable insights in order to promote innovative ideas on how to improve the effectiveness of the EU anti-manipulation law enforcement. We focus on the question of how to credibly deter market manipulation by AI trading by applying Deterrence Theory as an analytical tool. Within the field of Law and Economics, Deterrence Theory constitutes a branch of economic analysis that explores the interplay between different sanctions regimes and individual behaviour in abiding by the law. From a utilitarian perspective, this theory generally posits that an individual is more likely to break the law if the expected utility

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[726] *See* footnotes n. 312 and 400 and accompanying text. The term 'white collar crime' generally refers to a crime committed by a person who enjoys an apparently respectable and high social status in the course of his or her work. White-collar crimes are perpetrated by corporate officials as well as its subordinates. *See* John Braithwaite, 'White Collar Crime' (1985) 11 Annual Review of Sociology 1 <https://doi.org/10.1146/annurev.so.11.080185.000245> accessed 17 July 2024, offering a critical review of the various definitions provided in the white-collar literature.

[727] *E.g.*, Fox, Glosten, and Rauterberg (n 70).

[728] *See* Fletcher (n 71). This section specifically elaborates on the work by Gina-Gail S Fletcher, particularly the use of the Deterrence Theory in the case of algorithmic market manipulation. This dissertation, however, greatly advances the discussion on the topic by proposing a much more in-depth analysis.

derived from misconduct—measured as the difference between anticipated gains and associated costs—outweighs the utility of refraining from committing the offence.[729]

In the context of financial trading, Deterrence Theory suggests that rational human traders would refrain from engaging in unlawful conduct, such as market manipulation, unless the expected benefits outweigh expected costs. Simply put, if a human trader perceives a greater risk of penalties compared to economic rewards, he or she can be deterred from engaging in manipulation.[730]

According to this school of thought, the law can thus deter would-be manipulators by altering the balance of their expected utility derived market manipulation. By making market manipulation a costly and risky activity, the law diminishes the desirability of committing such offences from an *ex-ante* standpoint. When this is the case, deterrence is said to be *credible*, ensuring effective law enforcement. According to 'Deterrence Theory', there are two main variables that the law can leverage to alter the utility function of would-be wrongdoers: (*i*) the '*certainty of punishment*', that is the probability of being caught, investigated, prosecuted, and punished; and (*ii*) the '*severity of punishment*', which is the magnitude of the punishment, which may be either in monetary terms (e.g., a fine), time duration (e.g., a prison sentence), or other (e.g., a professional ban).[731]

(i) As a first variable, the '*certainty of punishment*' contributes to higher levels of deterrence by increasing individuals' perception of the likelihood of being punished. Several strategies can be employed to accomplish this objective.

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729 Ibid 267-268.

730Ibid.

731 *See, e.g.*, Raymond Paternoster, 'The Deterrent Effect of the Perceived Certainty and Severity of Punishment: A Review of the Evidence and Issues' (1987) 4(2) Justice Quarterly 173 <https://doi.org/10.1080/07418828700089271> accessed 17 July 2024.

First, legal systems must provide clearly defined legal prohibitions, establishing clear boundaries between legitimate and unlawful behaviours.[732] Uncertainty about the applicable law is undoubtedly one of the main reasons why the deterrence power of the law is not credible, thus favouring a general increase in offences. Additionally, credible deterrence relies on the resources, tools, expertise, and the authority of enforcers. In other words, enforcement authorities must possess the ability to detect, investigate, and prosecute offenders.[733]

(ii) As a second variable, the '*severity of punishment*' can contribute to credible deterrence of would-be offenders through the imposition of harsh penalties.[734] The magnitude of sanctions faced by offenders, such as lengthy sentences, significant monetary fines, or other punitive measures like professional bans, play a crucial role in deterring misconduct.[735] Therefore, the law should establish sufficiently high levels of punishment to discourage manipulative practices.

Over the years, the literature in Law and Economics has produced various models of the Deterrence Theory. Classical models generally support the idea that the

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732 Fletcher (n 71) 269.

733 *E.g.*, Carvajal and Elliott (n 646).

734 IOSCO, 'Credible Deterrence in the Enforcement of Securities Regulation' (June 2015) 35-40 <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD490.pdf> accessed 17 July 2024.

735 *See, e.g.*, A Mitchell Polinksy and Steven Shavell, 'The Optimal Use of Fines and Imprisonment' (1984) 24 Journal of Public Economics 89 <https://doi.org/10.1016/0047-2727(84)90006-9> accessed 17 July 2024.

law should focus on the 'severity of punishment' in order to optimally deter would-be offenders. The basic rationale is to make opportunities arising from misconduct unprofitable from an *ex-ante* perspective.[736] According to this approach, the law could therefore to deter individuals from attempting market manipulation by imposing substantial fines or other forms of punishment. However sensible this approach may seem, underlying classical models often fail to adequately capture the complexities of reality due to their overly simplistic assumptions.

On the one hand, these models disregard specific behavioural aspects that can influence individuals' motivations to commit offences. On the other hand, they ignore other aspects that may contribute to improving the ability of public authorities to successfully detect, prosecute, and punish misconduct. This limitation becomes particularly apparent in the context of AI-enabled forms of market manipulation, where the law is not dealing with rational human beings alone anymore, as envisioned in classical models.[737] The unique technical specificities of AI trading, powered by ML, require innovative approaches by the law to deal with the algorithmic behaviour. The latter, in fact, manifests and develops very differently from the behaviour of human traders, which implies that the law must use different tools to ensure credible deterrence against algorithmic market manipulation.

Recognising the limitations of classical models, new approaches emerged. These so-called Modern approaches, enriched by the fundamental insights of behavioural economics, appear better equipped to deal with forms of market manipulation involving AI trading. Behavioural aspects inherent to people propensity to misconduct and crime can provide valuable insights into the interplay between subjective elements,

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736 *See, e.g.*, Gary S Becker, 'Crime and Punishment: An Economic Approach' (1968) 76(2) Journal of Political Economy 169 <https://doi.org/10.1086/259394> accessed 17 July 2024, advancing an economic model for the analysis of criminal punishment in order to develop optimal public and private policies to fight illegal activities.

737 *Cf.* Arlen and Kornhauser (n 724) 683-688, discussing the shortcomings of classical Deterrence Theory models in dealing with sometimes irrational and however biased human beings.

which characterise the occurrence of market manipulation, and the law goal to achieve credible deterrence. In the context of AI trading, however, these behavioural aspects must be understood within the organisational context of investment firms adopting such tools, including all the human experts, both internal and external to a given organisation, participating the entire AI lifecycle. Nevertheless, according to Modern models, would-be manipulators are more sensitive to an increased probability of being punished rather than the magnitude of punishments. This effect can be attributed to, *inter alia*, ‘risk aversion’,[738] ‘loss aversion’,[739] and ‘punishment discounting’.[740] The effects of these behavioural components on the tendency of individuals to accept the risks associated with misconduct lead to the conclusion that prioritising the certainty of punishment over its magnitude represents the best strategy for ensuring credible deterrence.

Deterrence Theory, as a normative framework, serves as a valuable tool for designing effective liability rules and sanction regimes able to shape the inclination of individuals and their organisations to commit offences such as market manipulation.[741] As we shall see, the conceptual framework offered by Deterrence Theory can be applied as a useful toolkit to address the challenges inherent to deterring market manipulation in the context of AI agency.

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738 *See, e.g.*, Alex Raskolnikov, ‘Deterrence Theory: Key Findings and Challenges’ in Benjamin van Rooji and D Daniel Sokol, *The Cambridge Handbook of Compliance* (Cambridge University Press 2021) 185 <https://doi.org/10.1017/9781108759458.014> accessed 17 July 2024.

739 *See, e.g.*, Thomas A Loghran and others, ‘On Ambiguity in Perceptions of Risk: Implications for Criminal Decision Making and Deterrence’ (2011) 49(4) Criminology 1029, 1038-1039 <https://doi.org/10.1111/j.1745-9125.2011.00251.x> accessed 17 July 2024. The term ‘loss aversion’ describes a cognitive bias according to which individuals psychologically perceive the pain from a loss to a greater extent than the pleasure from a gain. *See* Daniel Kahneman, Jack Knetsch, and Richard H Thaler, ‘Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias’ (1991) 5(1) Journal of Economic Perspectives 193 <https://www.jstor.org/stable/1942711> accessed 17 July 2024.

740 *See, e.g.*, A Mitchell Polinsky and Steven Shavell, ‘On the Disutility and Discounting of Imprisonment and the Theory of Deterrence’ (1999) 28(1) The Journal of Legal Studies 1 <https://www.jstor.org/stable/10.1086/468044> accessed 17 July 2024.

741 *See, e.g.*, Fletcher (n 71).

A. Market manipulation by AI as corporate misconduct and crime

While ML methods and related applications are becoming increasingly accessible to the public, it is important to note that only well-resourced and professional traders possess the means to employ the most advanced strategies and techniques. Therefore, for the purpose of our analysis, it is reasonable to consider the most sophisticated forms of AI market manipulation as specific instances of corporate financial misconduct and crime.[742]

Corporate misconduct or crime typically involve one or more employees within an organisation who, within the scope of their employment, are motivated to commit offences with the intention of benefiting the organisation. The causes behind such pathological corporate behaviours can vary greatly, with instances of market manipulation often arising as the consequence of internal cultural factors within investment firms. For instance, unethical senior management or other agency problems that may emerge within an organisation can largely contribute to the occurrence of such wrongdoings.[743] Unlike individual misconduct and crime, the law requires alternative strategies to regulate and constrain individuals' behaviours when they are part of an organisation—commonly referred to as 'corporate behaviour'.

In principle, firms can either encourage or discourage the occurrence of market misconduct. On the one hand, they can facilitate malpractices through, for instance, specific compensation schemes that incentivise their employees to engage in unlawful acts. On the other hand, they can inhibit potential wrongdoers by cooperating with public authorities in enforcement efforts. In light of this risk, some Modern theories of

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742 This assumption is justified by the fact that successful forms of market manipulation by AI trading require high market access capability and, however, can entail substantial transaction costs and expose to risks of financial losses. All these conditions seem therefore to suggest that only well-resourced and sophisticated market actors can be involved in cases of algorithmic market manipulation.

743 *See* Jennifer Arlen and William J Carney, 'Vicarious Liability for Fraud on Securities Markets: Theory and Evidence' (1992) 1992(3) University of Illinois Law Review 691 <https://ssrn.com/abstract=2042097> accessed 17 July 2024.

deterrence emphasise the important role of 'corporate criminal liability' as a liability rule that contributes to enhancing deterrence. According to these approaches, 'corporate criminal liability' can serve as a tool to incentivise firms to cooperate with enforcement authorities, thereby bolstering the effectiveness of law enforcement. This view recognises that public authorities alone cannot prosecute all offences.[744] It also identifies the strategy exclusively focused on setting high monetary fines (or other punishments) as another main limitation to effective deterrence.[745] Moreover, since law enforcement entails social costs, supporters of this approach believe that a portion of these costs should be borne by the private organisations themselves.[746]

From a deterrence perspective, legal rules governing corporate liability can be seen as a complementary tool to individual liability, rather than a mere substitute.[747] Governments around the globe also acknowledge the essential role played by corporate (criminal) liability in combating complex economic misconducts and crimes,[748] such as market manipulation. Corporate criminal liability aims to ensure that both individuals and organisations that benefit from wrongdoings perpetrated by their employees can be held accountable and liable for misconduct. By making legal persons (i.e. investment firms) potential targets of law enforcement, corporate criminal liability empowers investigations, judicial or administrative proceedings, and ultimately sanctions against corporations found (co-)responsible for economic misconducts or

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744 *See* Jennifer Arlen, 'Corporate Criminal Liability: Theory and Evidence' in Alon Harel and Keith N Hylton (eds) Research Handbook on the Economics of Criminal Law (Edward Elgar Publishing 2013) 162-167.

745 *E.g.*, Arlen and Kornhauser (n 724) 724.

746 *See* footnote n. 744.

747 *See* ibid 167-172; *see also* Vikramaditya S Khanna, 'Corporate Criminal Liability: What Purpose Does It Serve' (1995) Harvard Law Review 1477 <https://doi.org/10.2307/1342023> accessed 17 July 2024, who however argues in favour of corporate civil liability rules as opposed to those under criminal law.

748 *See* OECD, 'The Liability of Legal Persons for Foreign Bribery: A Stocktaking Report' (2016) <https://www.oecd.org/daf/anti-bribery/Liability-Legal-Persons-Foreign-Bribery-Stocktaking.pdf> accessed 17 July 2024.

crimes. Under this perspective, therefore, corporate liability proves particularly valuable in achieving effective enforcement in the context of AI market manipulation, especially when the latter is conceived as a form of corporate misconduct or crime.

The contribution of corporate criminal liability to law enforcement outcomes can be viewed from two perspectives. First, it enables public authorities to hold legal persons liable for specific wrongdoings either in addition or independently from any involvement of natural person in any given case of market manipulation. Second, the exact design of liability rules can create efficient incentives for investment firms to adopt virtuous and cooperative behaviours, which can support the tasks of public authorities by reducing their efforts in the detection, prevention, investigation, and resolution of market abuse.[749]

Against this backdrop, we must also bear in mind that the primary objective of an efficient and credible deterrence regime is to minimise the overall costs associated with an offence. These costs encompass not only the harm inflicted upon victims and the market, but also the expenses incurred through enforcement activity. The latter include both direct costs borne by enforcement authorities and the societal costs resulting from potential over-deterrence due to inaccurate prosecution and other legal errors.[750]

Given the inherent risks posed by AI trading, the development of an effective enforcement regime to deter market manipulation should be a top priority on the policy agenda of EU legislators.[751] Ineffective enforcement, in fact, leaves markets

749 Ibid.

750 *See* Amanda M Rose, 'The Multienforcer Approach to Securities Fraud Deterrence: A Critical Analysis' (2010) 158 University of Pennsylvania Law Review 2173, 2183-2193 <https://scholarship.law.vanderbilt.edu/faculty-publications/603> accessed 17 July 2024, who highlights the main factor responsible to ultimately determine the magnitude of overdeterrence costs.

751 Frank H Easterbrook and Daniel R Fischel, 'Mandatory Disclosure and the Protection of Investors' (1984) 70 Virginia Law Review 674 <https://chicagounbound.uchicago.edu/cgi/viewcontent.cgi?article=2176&context=journal_article>

vulnerable to widespread and unpunished market manipulation, which can impose a significant burden on society in terms of lost welfare. Consequently, legal systems must equip regulators with the necessary legal tools and resources to counterbalance the technological advantages enjoyed by the industry.[752]

Notwithstanding all the above-mentioned challenges to effective enforcement, financial regulators worldwide concur on the criticality of credible deterrence for achieving effective law enforcement in capital markets.[753] In a nutshell, deterrence is deemed credible when it can modify behaviours of market participants and reduce violations. Moreover, deterrence is considered effective when it ensures the detection, prosecution, and sanctioning of misconduct.

B. Some preliminary thoughts on the direct deterrence of AI

AI trading poses new and fundamental questions regarding the prevention of market misconduct, particularly on how to ensure credible deterrence through adequately structured liability rules and sanctions. An effective enforcement regime, in fact, must persuade market participants to abstain from market manipulation by threatening them with sanctions or other penalties. Yet, optimal deterrence is achieved when it not only dissuades investment firms and their staff from engaging in misconduct but also motivates them to take precautionary measures and support enforcement actions when manipulation occurs. Thus, an effective enforcement regime not only reduces the risks of misconduct to optimal levels but also minimises the societal costs associated with enforcement.

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accessed 17 July 2024, who advocate the fundamental role of market abuse regulation as more efficient than exclusive reliance on market-based solutions.

752 *See, e.g.*, Carvajal and Elliott (n 646).

753 *See, e.g.*, IOSCO (n 734) 10-54. The report highlights seven key factors for ensuring credible deterrence, including: (i) legal certainty, (ii) strong supervisory frameworks, (iii) institutional cooperation and collaboration, (iv) robust enforcement, (v) strong punishments, (vi) public awareness, and (vii) effective regulatory governance.

However, the presence of AI agency fundamentally alters the challenge of deterring market manipulation in significant ways. Given that advanced AI systems should be conceived as complex 'human-machine' hybrid systems, they represent a usual *animal* to regulate. Unlike human or corporate conduct, shaping the behaviour of AI trading systems entails a distinct set of difficulties for the law.[754] These systems, operating as complex ecosystems of algorithms in highly interconnected market environments, often exhibit behaviour that are fundamentally different from those of human traders.[755] For this reason, the law may lack effective tools to shape AI behaviour. Due to ML, in fact, AI trading systems can often behave as black boxes, further complicating matters of behavioural regulation and control.

The 'knowledge gap' faced by financial regulators exposes legal systems to substantial risks of under-deterrence. In contrast, AI-powered trading can operate within a quasi-lawless environment, enabling manipulative actions to go undetected with a high likelihood of evading legal consequences. In this context, certain market actors may—more or less consciously—externalise the costs of their manipulative conducts to society. Despite all these challenges for enforcement, in the author's opinion it is still possible to leverage 'Deterrence Theory' as a theoretical framework for developing innovative regulatory solutions that are better able to address AI market manipulation.

A potential idea for deterring market manipulation by AI could entail the direct integration of a 'deterrence formula' into the system's cost-benefit utility function.[756] This approach, however, hinges on the establishment of a well-defined legal framework

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754 *See* Iyad Rahwan and others, 'Machine Behaviour' (2019) 568 Nature 477 <https://doi.org/10.1038/s41586-019-1138-y> accessed 17 July 2024.

755 *Cf.* ibid 483.

756 This 'deterrence formula', in the form of a constraint function intended to shape and control the behaviour of a given AI system, should ensure AI alignment with user intended goals, including compliance with regulatory requirements. *Cf.* Turner (n 699) 361.

that clearly delineate the boundaries permitted conduct and enables the translation of these boundaries into objective and quantifiable constraints that can be programmed into AI systems. For this reason, the operationalisation of such a technical solution faces significant legal as well as practical limitations. Given the uncertain feasibility of deterring AI *ex-ante*, the merits of *ex-post* forms of punishment thus remain to be explored. In this case, though, there is the question of which persons the law should target punishment on in order to ensure credible deterrence.

One often debated idea in the context of AI misconduct or crime is that of punishing AI itself.[757] Now, the main limitation of such a proposal lies in the fact that AI does not enjoy the personhood status in law. AI cannot be sued in court and holds no assets.[758] Through a legal fiction, one can consider AI as a legal person, as is the case with corporations.[759] However, this option raises a multitude of ethical-legal issues.[760] For example, the recognition of AI systems as legal entities leaves unanswered several questions about how to ensure accountability and the allocation of legal rights and obligations related to AI acts.[761] More generally, especially from a conceptual point of view, deeming AI an agent per se does not seem reasonable. At the end of the day, AI systems are always working for humans, and their operation is somewhat determined by programming.[762]

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757 *See, e.g.*, Ying Hu, 'Robot Criminals' (2019) 52(2) University of Michigan Journal of Law Reform 487 <https://doi.org/10.36646/mjlr.52.2.robot> accessed 17 July 2024, which supports the idea that criminal liability could be attributed directly to AI systems. The author also discusses some possible punitive alternatives applicable to the criminal AI context.

758 *E.g.*, King and others (n 699) 108-109; Pınar Çağlayan Aksoy, 'AI as Agents' in Larry A Di Matteo, Cristina Poncibò, and Michael Cannarsa (eds), *The Cambridge Handbook of Artificial Intelligence: Global Perspectives on Law and Ethics* (Cambridge University Press 2022) 159-160 <https://doi.org/10.1017/9781009072168.016> accessed 17 July 2024.

759 *E.g.*, Hallevy (n 562) 103.

760 *See generally* Chesterman (n 699).

761 *See, e.g.*, Calo (n 699) 538-545; Abbott and Sarch (n 665) 152-156.

762 *E.g.*, Matthew Oliver, 'Contracting by Artificial Intelligence: Open Offers, Unilateral Mistakes, and Why Algorithms are not Agents' (2021) 2(1) Australian National University Journal of Law and

From a policy standpoint, given the current stage of AI technology, it may be thus more pragmatic and desirable to hold firms and individuals accountable, responsible, and liable for any harm caused by their AI systems.[763] This approach ensures that the responsibility lies with human actors who develop, deploy, and oversee AI applications.[764] Nonetheless, the feasibility and desirability of deterring AI *ex-ante* (i.e. prior to the occurrence of harm) and punishing AI *ex-post* (i.e. after harm has been caused) necessitate further in-depth discussion and exploration within the scientific and regulatory arena. In the following, we provide some preliminary idea on these two alternative approaches that could potentially enhance the credibility of deterrence against market manipulation by AI trading.

i. Deterring AI ex-ante

Being able to deter, *ex-ante*, AI from engaging in market manipulation through technical solutions designed to control its market conduct would be incredibly useful. Given that the core functioning of AI systems, powered by ML, is deeply rooted in solving mathematical optimisation problems, there may be an opportunity to explore ways by which to integrate a 'deterrence formula' within their inner workings. Such a technical solution would entail incorporating market conduct rules into AI trading models, aiming to instruct AI systems on how to avoid engaging in non-permissible market conduct.

Let us suppose there were no technical or legal obstacles impeding the implementation of such a solution through programming codes. Even then, the autonomous and self-learning nature of certain AI systems, thanks to ML, would encounter difficulties in adapting to evolving regulations and market dynamics,

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Technology 45, 50 <https://anujolt.org/article/24466-contracting-by-artificial-intelligence-open-offers-unilateral-mistakes-and-why-algorithms-are-not-agents> accessed 17 July 2024.

[763] *See, e.g.*, Feldman and Stein (n 94) 122-125.

[764] *E.g.*, ibid 129-131.

thereby compromising their ability to ensure deterrence in a dynamically credible manner. Perhaps, regulatory technology, or RegTech[765], solutions such as machine-readable regulation and compliance may overcome some of these limitations.[766] The idea is that machine-readable and machine-executable rules can be transmitted to AI trading systems, which will then operate in the markets within the limits allowed by these rules to be legally compliant. Nevertheless, a crucial prerequisite for this approach is the establishment of regulatory expectations that are objective and quantifiable, enabling AI trading systems to process and interpret them accurately. Unfortunately, the current legal prohibitions on market manipulation suffers from a certain level of vagueness regarding their objective elements, thereby providing ample room for legal interpretation. Moreover, in order to programme a 'deterrence formula', human experts would need to rely on specific methodologies to effectively quantify both the 'severity of punishment' and 'certainty of punishment' elements of deterrence. Consequently, the existing definitions of market manipulation, as well as the related enforcement rules and mechanisms, do not lend themselves to AI trading systems effectively calculating the utility of engaging in market misconduct and subsequently being deterred from doing so.

ii. Punishing AI ex-post

While technical solutions for *ex-ante* deterrence of AI miscount may be difficult to implement, the legal possibility of *ex-post* punishment is another interesting

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765 *See* Douglas W Arner, Janos Barberis, and Ross P Buckley, 'FinTech, RegTech, and the Reconceptualization of Financial Regulation' (2016) 37 Northwestern Journal of International Law & Business 371, 373 <https://scholarlycommons.law.northwestern.edu/njilb/vol37/iss3/2> accessed 17 July 2024, defining RegTech as "*the use of technology, particularly information technology, in the context of regulatory monitoring, reporting, and compliance*."

766 On the role of RegTech for regulatory compliance, see Tom Butler and Leona O'Brien, 'Understanding RegTech for Digital Regulatory Compliance' in Theo Lynn and others (eds), *Disrupting Finance: FinTech and Strategy in the 21st Century* (Palgrave Macmillan 2019) 85-102 <https://doi.org/10.1007/978-3-030-02330-0_6> accessed 17 July 2024; *see also* Jakob Schemmel, 'Artificial Intelligence and the Financial Markets' in Thomas Wischmeyer and Timo Rademecher (eds), *Regulating Artificial Intelligence* (Springer Cham 2020) 268-269 <https://doi.org/10.1007/978-3-030-32361-5_11> accessed 17 July 2024.

alternative to explore.[767] However, the concept of '*punishing AI ex-post*' raises intricate questions. Mainly, *can we retrospectively impose punishment on AI systems for their misconduct?* For many commentators, one major legal obstacle to operationalise this alternative is the absence of legal personhood recognition for AI within existing legal systems.[768] As such, legal systems face significant challenges in enforcing the law directly against AI itself in cases of offences and related harm.[769] Even if we momentarily entertain the idea of granting legal personhood to AI systems, the application of established legal concepts of liability would remain arduous. For instance, the criminal law requirement of 'intent', known as '*mens rea*', poses complexities when applied to AI-induced forms of crime,[770] including serious cases of market manipulation. Also, the legal concept of 'causation' struggles to address issues of liability attribution for AI misconduct.[771]

Beyond these general legal considerations, the design of an appropriate punishment regime targeting AI presents critical challenges. For instance, the notions of temporarily banning an AI system from its professional activity or sentencing it to a period of incarceration has been proposed in the literature, especially in the case of robots.[772] But these traditional punitive options applicable to individuals, such as imprisonment or professional ban, are not fully functional in the case of AI. Analogous alternatives seem more appropriate, such as shutting down or temporarily suspending operation of a specific model, component, or system. Once again, however, such policy

[767] *See* footnote n. 757 and 759.

[768] *See* footnote n. 758 and 760.

[769] Ibid.

[770] *See* discussion in Chapter 6.2.C; *see also* Abbott and Sarch (n 665) 349-360.

[771] *See* discussion in Chapter 6.2.A; *see also* Turner (n 699) 57-63.

[772] *See* Hallevy (n 562) 219-221; Hu (n757) 529.

alternatives may face some impediment in their application.[773] Requiring an investment firm to 'switch off' or temporarily suspend the operation of an AI trading system, or only some parts of it, as a sanction lacks credibility and reasonableness. The potential for technical workarounds to circumvent such measures cannot be ignored. An investment firm could easily modify certain components of an AI algorithm or system to create the impression of compliance with market conduct rules. Similarly, imposing monetary fines as punishment for AI is also an unconvincing option. Since AI lacks legal personality and cannot hold assets, this approach becomes hardly impracticable.

In sum, within the context of existing legal frameworks, the idea of granting legal personhood to AI proves to be a complex conceptual and legal issue, making the notion of AI punishment difficult to put into practice. At the same time, while the idea of deterring AI through programming could be an interesting technical solution to explore, it also faces a number of challenges to be successful adopted. These considerations lead us to conclude that, when it comes to accountability and liability for misconduct and harm involving AI, the responsibility should primarily lie with the individuals and their respective organisations involved in its design, develop, deploy, use, and maintenance. The law must target those individuals and organisations that derive benefits from AI.[774] Building on this finding, in the next section we provide some preliminary thoughts on possible policy measures to improve the current market conduct enforcement regime within the EU, able to ensure credible deterrence.

6.5 Towards Credible Deterrence of AI Market Manipulation

Due to ML, AI trading and its potential to disrupt market integrity call into question the effectiveness of the EU marker abuse enforcement regime. The quasi-lawless

[773] *Cf.* Mark A Lemley and Bryan Casey, 'Remedies for Robots' (2019) 86(5) The University of Chicago Law Review 1311, 1389-1392 <https://www.jstor.org/stable/10.2307/26747441> accessed 17 July 2024.

[774] *E.g.*, Abbott and Sarch (n 665) 378-379.

market environment in which AI trading operates amplifies risks of rigged markets, which in turn may threaten the stability of the whole system. With this in mind, EU policymakers and financial regulators are called to assess their actual ability to counter the risks associated with AI trading, especially given the technical specificities of specific ML methods and the still fragmented nature of enforcement mechanisms. Indeed, the rapidly changing market landscape due to technological innovation in AI may warrant reforms to current regulatory regimes on the governance of algorithmic trading and the fight against market manipulation.

From this perspective, this section presents several policy proposals *de lege feranda*, which intend to offer solutions to the challenge of deterring AI market misconduct and crime. These preliminary ideas for reform build upon the current EU MAR/MAD enforcement regime with a view a strengthening it. In this section, we therefore focus on enforcement issues, particularly how to design liability rules and enforcement regimes capable of ensuring credible deterrence against market manipulation by AI trading. We must, however, recognise that market conduct supervision is also an integral part of a robust and effective enforcement regime. But this other matter will be specifically addressed in Chapter 7. Thus, in what follows we propose and discuss two main solutions to strengthen the deterrent effect of the EU enforcement regime: (A) an enhanced definition of market manipulation that adopts a 'harm-centric' approach, and (B) an improved multi-level liability framework at EU level.

A. An improved, 'harm-centric' definition of market manipulation

The existing definitions of market manipulation, as previously examined, may be unable to ensure legal certainty in the context of AI trading, since their application is encapsulated in the determination of intent or other relevant mental state, such as negligence, of wrongdoers. It is worth reiterating that the enforcement of market conduct rules has long been accompanied by inherent difficulties, even during times dominated by human trading. Given that algorithmic trading now accounts for most of total market activity, overshadowing the traditional role of human traders, the gravity of this issue has reached disconcerting proportions.

As an idea already advanced in the literature, one potential solution to address enforcement issues would be adopting a more precise and harm-centric definition of market manipulation.[775] The underlying premise is that by embracing an enhanced 'harm-based' definition, market participants would be able to rely on more objective and quantifiable elements in discerning illicit trading activity from legitimate practices. Such a definition would provide market participants with greater legal certainty regarding the clear boundaries demarcating prohibited trading conduct. At the same time, a harm-based definition would provide law enforcement authorities with a more reliable legal framework, including better defined legal tests, for addressing cases of market manipulation. Likewise, a harm-based definition could also ease the process for victims seeking legal remedies and compensation for their losses, as cases of market manipulation could become easier to identify, while their effects would be more easily measured in numerical terms.[776]

Moving to a 'harm-based' definition of market manipulation presents several advantages, yet it necessitates delicate policy considerations by policymakers. Of

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[775] *See, e.g.*, Albert S Kyle and S Viswanathan, 'How to Define Illegal Price Manipulation' (2008) 98(2) American Economic Review 274 <https://www.aeaweb.org/articles/pdf/doi/10.1257/aer.98.2.274> accessed 17 July 2024, arguing that trading practices should be classified as illegal when they cause inaccurate price and illiquid markets; Matthijs Nelemans, 'Redefining Trade-Based Market Manipulation' (2008) 42(4) Valparaiso University of Law Review 1169 <https://scholar.valpo.edu/vulr/vol42/iss4/4> accessed a7 August 2023, proposing a definition of market manipulation according to the measurable effect on prices of a given practice that is not justified by relevant information; Fletcher (n 75) 519, proposing a definition of market manipulation based on the harm that given practices cause to markets; Daniel W Slemmer, 'Artificial Intelligence & Artificial Prices: Safeguarding Securities Markets from Manipulation by Non-Human Actors' (2019) 14(1) Brooklyn Journal of Corporate, Financial & Commercial Law 149 <https://brooklynworks.brooklaw.edu/bjcfcl/vol14/iss1/11> accessed 17 July 2024, arguing that the definition of market manipulation should take into account the observable effects on market prices associated with a given conduct; Barr and others (n 344), advocating a definition of market manipulation that is devoid of subjective elements and focused on the effects of specific trading behaviours.

[776] *E.g.*, Slemmer (n 775) 161-165; Fletcher (n 75) 318-320; Barr and others (n 344) 21-23.

utmost importance is the establishment of a comprehensive framework that delineates market manipulation from a 'harm-centric' perspective. In this last regard, some economic research has sought to disentangle the concrete objective elements of certain manipulative practices from any subjective element. One potential solution, for instance, involves defining 'trade-based' market manipulation as any trading activity that exerts unjustified pressure on market prices due to an absence of adequate supporting information.[777] This approach, however, operates under the assumption that certain market activities neither contribute to nor enhance the informativeness of market prices, as they are carried out regardless of publicly available fundamental information. According to this definition of market manipulation, those trading activities that create unsupported price pressure are not motivated by economically efficient logic. And, as such, they can be framed as harmful practices, often resulting in manipulative practices that prioritise private gains at the expense of the public goals of market quality and integrity.[778]

However, adopting a harm-based definition of market manipulation presents substantial challenges. Primarily, categories and measures of harm need to be unambiguously specified. This turn out to be of paramount importance to trigger enforcement action, as regulators would need to provide compelling evidence to successfully prosecute misconducts. This, for instance, could entail demonstrating that the suspected parties did not have sufficient and adequate information to justify their trading behaviours.[779] Nonetheless, this necessitates financial regulators to establish a legal framework that clearly defines what constitute adequate information to justify a given trading activity—a task that is far from straightforward. Additionally, market supervisors would require specific methodologies and tools to effectively identify harm

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[777] *See* Nelemans (n 775) 1178-1190.

[778] Ibid 1190-1198.

[779] Ibid 1210-1217, examining the relationship between trading, market information, price pressure and price change. The author also discusses methods that regulators could use to produce evidence of unsupported price pressure.

and attribute liability based on the precise contribution of the alleged wrongdoers.[780] Nevertheless, a 'harm-based' definition of manipulation holds the potential to signal to market participants the types of market conduct that financial authorities deem lawful, thereby fully leveraging the expressive role of the law.[781]

Reforming the definition of market manipulation with an improved version that emphasises the impact on markets, rather than solely relying on the underlying motives behind specific trading conducts, could serve as a means to achieve credible deterrence of AI trading manipulation. By adopting more objective and quantifiable definitions, AI trading systems could be programmed to consider the numerical boundaries delineated by an enhanced definition of market manipulation while pursuing optimisation tasks aligned with specific business goals. Arguably, a more objective and quantifiable definition of manipulation could also facilitate the research of technical solutions for allowing ex-ante deterrence of market manipulation by AI trading.

Although regulatory reforms of the prohibition of market manipulation are not seen on the horizon, it should still be noted that at least EU legislators have been committed to providing more clarity to market participants about the harmful effect of certain practices. In this regard, for instance, the definition of 'indicators' of market manipulation through Commission Delegated Regulation (EU) 2016/522 can be viewed as a positive first step towards greater legal certainty.[782] However, due to the challenges posed by AI trading, there remains considerable room for future research and improvement.

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780 *E.g.*, ibid; Slemmer (n 775) 169-174; Fletcher (n 75) 318-320.

781 *Cf.* Nelemans (n 775) 1176.

782 Although these 'indicators' of manipulation are not defined into numeric or statistical values, they are nonetheless useful in providing examples of suspicious signs associated with various manipulation strategies. *Cf.* Commission Delegated Regulation 2016/522 (n 538).

As the main takeaway from the above, financial law and regulation, particularly market conduct rules in times of AI trading, should always be grounded upon the most up-to-date scientific knowledge of capital markets and their behavioural functioning.[783] To this end, financial regulators must be equipped with the requisite expertise, motivation, and public support to understand intricate network systems—such as global algorithmic capital markets—comprehensively and pragmatically. Indeed, the effort to determine what trading practices are accepted by AI cannot be left to AI practitioners and users alone.[784] However, to overcome the complexities inherent in trading with AI, particularly with regard to the underlying ML methods, there is a need to strengthen cooperation across scientific fields to develop an interdisciplinary understanding of the interplay between ML methods, algorithmic market behaviour, and the associated effects on markets. This, in turn, underscores the urgent need for regulators to establish multi-stakeholder collaboration as a necessary element of an effective regulatory approach able to address the multiple challenges associated with market manipulation in the AI era.

B. An improved, 'multi-layered' liability framework

In conjunction with a 'harm-based' definition of market manipulation, we explore here the merits of establishing new liability rules that may be better tailored to address AI-induced market manipulation. As argued above, current liability rules are not optimal for achieving credible deterrence. AI agency introduces an additional layer of complexity, resulting in a 'knowledge gap' for enforcement authorities. This gap translates into issues of human accountability and liability whenever AI-enabled misconducts or crimes occur. Moreover, while liability rules traditionally aim to shape

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[783] *Cf.* David C Donald, 'Regulating Market Manipulation trough an Understanding of Price Creation' (2011) 6 National Taiwan University Law Review 55, 82 <https://ssrn.com/abstract=1667457> accessed 17 July 2024.

[784] *See, e.g.*, Ashton (n 708) 8, arguing that any definition of AI-related side effects should be based on principles and values established by society.

human behaviour towards socially acceptable conduct, they are ill-equipped to effectively deal with the specific features of AI misbehaviour, due to ML.

The following proposes an improved 'multi-layered' liability framework for AI misconduct, encompassing both administrative and criminal liability. This framework would differentiate liability rules and sanctions based on varying degrees of harm and level of human involvement.[785] The objective of this proposed multi-layered liability framework, which disentangles administrative and criminal liability aspects pertaining to AI misconduct, is twofold. First, it aims to ensure that investment firms exercise due diligence in their use of AI trading systems by, for instance, adequately investing in precautionary measures. At the same time, it should also incentivise trading venues to police the use of trading algorithms by clients on their platforms. Second, it seeks to foster close collaboration between market participants and public authorities to prevent misconduct from occurring in the first place. In cases where misconduct does occur, the framework should provide strong incentives for multi-stakeholder collaboration in enforcement action.

i. Criminal liability

In cases of intentional and serious violations, criminal liability should continue to apply, regardless of whether they stem from traditional manipulative schemes or by AI-powered algorithmic trading strategies.[786] However, since we cannot hold AI systems themselves criminally liable, a fundamental question arises: *Who should be held accountable for AI misconduct and the resulting harm?*

[785] *Cf*. Feldman and Stein (n 94) 128-131.

[786] *See, e.g.*, ibid 128; Ashton (n 708) 8.

Some scholars argue that individual criminal liability is already a suitable tool to regulate and prevent market misconduct in the realm of algorithmic trading.[787] According to this view, there are two primary reasons for advocating individual criminal liability over corporate criminal liability. On the one hand, holding individual human experts, such as traders and those responsible for control and risk management functions, directly accountable for algorithmic trading misconduct would have a stronger deterrence effect compared to relying on corporate criminal liability.[788] On the other hand, the burden of proof in criminal proceedings is higher than in administrative or civil trials. A criminal conviction of an individual necessitates more stringent evidentiary standards. These higher procedural thresholds are intended to ensure that prosecutors target and punish only the most severe offences.[789] However, this line of reasoning may encounter some important limitations. Mainly, ascertaining and attributing liability for specific AI misbehaviours to responsible individuals can be an extremely burdensome tasks, and sometimes it may even be unfeasible.[790]

Due to the substantial complexity embedded in AI systems as 'hybrid' human-machine entities, observing and regulating AI trading behaviour poses intricate challenges. Rather, a more feasible and safer approach might be to attribute the implications of the market misconduct of AI trading systems and the associated effects on markets directly to the investment firms that is in *control* and *benefit* from these systems. Thus, the law should recognise AI trading conduct as a corporate action,[791]

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787 *See* Orlando Cosme, 'Regulating High-Frequency Trading: The Case for Individual Criminal Liability' (2019) 109 Journal of Criminal Law and Criminology 365 <https://scholarlycommons.law.northwestern.edu/jclc/vol109/iss2/5> accessed 17 July 2024.

788 Ibid 387-388.

789 Ibid 383-385.

790 *See* discussion in Chapter 6.1.A-B.

791 *See* Mihailis Diamantis, 'Algorithms Acting Badly: A Solution from Corporate Law' (2021) 89 The George Washington Law Review 801, 827-830 and 844-849 <https://www.gwlr.org/wp-content/uploads/2021/07/89-Geo.-Wash.-L.-Rev.-801.pdf> accessed 17 July 2024.

akin to how the acts or omissions of employees can be imputed to corporations. Through this legal technique, it is possible to close the accountability gap associated with AI by keeping humans accountable and liable for misconduct or crime by AI trading.

However, even when imputing AI misconduct as a corporate action, a distinction needs to be made regarding conducts that give rise to criminal liability and those that do not. As previously discussed, the concept of 'intent' does not align well with attributing liability for AI market manipulation. Instead, 'fault-based' liability standards such as 'recklessness' could offer a more suitable alternative.[792] It is worth mentioning that MAD itself does not exclude the possibility of applying fault-based liability rules for market manipulation crimes.[793]

Under a recklessness standard, liability would arise when a person deliberately and without justification pursues a course of action while consciously disregarding the risks associated with such conduct. In a nutshell, the concept of recklessness describes a situation in which a person has failed to care as a reasonable person would do given the risks at stake.[794] Recklessness as a liability rule seems best suited to strike a balance between the level of care required given the complex technical nature of certain ML-based AI systems, the risks to markets resulting from occurrences of manipulation, and the need to keep humans accountable and liable for the operation of these systems.

Whenever AI is involved in market manipulation, a recklessness standard, as opposed to intent, could facilitate the assessment of the *means rea* element of a corporation, particularly its employees in key position responsible for oversight,

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792 *See* Slemmer (n 775) 174-177; Fletcher (n 125) 320–321.

793 *Cf.* MAD recital (21).

794 *See, e.g.*, Peter Cane, 'Mens Rea in Tort Law' (2000) 20(4) Oxford Journal of Legal Studies 533, 535-538 <https://doi.org/10.1093/ojls/20.4.533> accessed 17 July 2024, discussing the core conceptual differences between intention, recklessness, and negligence.

compliance, and the development or use of AI systems.[795] However, the application of a recklessness standard requires the measurement of human conduct based on predetermined and widely accepted practices, which may be defined through industry standards, regulations, or a mix thereof. Moreover, the assessment of recklessness should cover various governance aspects related to the AI lifecycle, including the design, development, use, control, and oversight of AI systems and their operation in the markets.[796] Below, we discuss the advantages of this approach through an illustrative example.

- *Case study*

When determining liability for AI market manipulation, a recklessness standard can be applied to assess the *means rea* element of a corporation, particularly its employees in key position responsible for the development, use, oversight, and regulatory compliance of AI systems. To understand the advantages of a recklessness liability rule, consider the following scenario. Suppose market conduct supervisors have identified a suspicious case of market manipulation executed by sophisticated AI trading strategies employed by a specific investment firm. When questioned about the event, the firm would have to provide, in order to escape liability, a convincing explanation with documented evidence of the goodness of the behaviour of the AI system in question. This explanation must convince the authorities that all appropriate precautions were taken and that the alleged manipulative conduct was actually justified by valid and legitimate business reasons.

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795 *See, e.g.*, Slemmer (n 775) 175-176; Abbott and Sarch (n 665) 378-381; Fletcher (n 75) 321.

796 A similar approach, encompassing a fault-based regime of liability for AI, is also pursued by the recently proposed AI Liability Directive according to which, whenever users and providers of AI systems fail to comply with the various requirements set forth in the AI Act, they are presumed to have failed to meet their duty of care. For a critical account, see Marta Ziosi and others, 'The EU AI Liability Directive: Shifting the Burden from Proof to Evidence' (2023) SSRN preprint 1 <https://ssrn.com/abstract=4470725> accessed 17 July 2024.

In such a context, a ‘recklessness’ standard of liability would enable the burden of proof to shift from enforcement authorities to the defendants for the alleged misconduct, which would bear the responsibility of demonstrating that their use of AI was not reckless in nature.[797] With the reversal of the burden of proof, the expectation is that those using AI systems will also be strongly incentivised to develop a corporate culture that aligns with the public goal of safe AI and market integrity.

The proposed example confronts us with three main hypothetical scenarios: (*a*) ‘Collaboration’, the investment firm adopts a virtuous and cooperative stance; (*b*) ‘Contention’, the investment firm is ready to fiercely contest the allegations; and (*c*) ‘Deficient explanation (or obvious fault)’, the investment firm is in an unfavourable position, being unable to provide explanations regarding the misbehaviour of its AI trading system.

a. Collaboration

In the first—perhaps less realistic—scenario, let us consider a collaborative approach by the investment firm. In this scenario, the investment firm identifies and reports its failure to adequately implement precautionary measures (e.g., risk management or other control activities) or acknowledges manipulative practices performed by its AI trading system. Misconduct by AI may thus be due to intentional or negligent behaviour on the part of some investment firm employees. In any case, the threat of corporate criminal liability may serve as an incentive for the firm to self-condemn and cooperate in enforcement action. While, based on a recklessness standard, the investment firm is held liable, as a next step, it may internally ascertain the exact contribution to liability of individual employees according to their exact role along the AI production line.

b. Contention

[797] *See, e.g.*, footnote n. 795.

Moving on to the second scenario, we find an investment firm that adopts a less collaborative stance. Rather, the firm firmly believes that it has implemented all necessary precautionary measures, including maintaining adequate supervision and control over AI trading to ensure compliance. Additionally, it contends that its AI trading activities did not result in unlawful conduct, attributing any harm to possibly complex interactions among competing algorithms in the market. In this scenario, enforcement authorities would need to demonstrate that the investment firm failed to exercise the appropriate duty of care, resulting in a faulty implementation of AI trading. In order to apply a recklessness standard, however, enforcers would require a well-defined framework to assess liability. Assuming that a clear methodology is available, the burden of proof can still be shifted to the defendant. Thus, whenever the investment firm would not be in a position to credibly demonstrate their safe and responsible use of AI trading technology, enforcement authorities would have enough elements to demonstrate a reckless conduct. Whenever this is the case, 'corporate criminal liability' will be automatically triggered and the firm will be found liable for the AI-enabled misconduct.

c. Deficient explanation (or obvious fault)

In the third scenario, we observe an investment firm that fails to provide a convincing explanation about misbehaviour on the part of its AI trading system. In all such cases, law enforcement authorities do not confront major problems in proving the liability of investment firms. In fact, the latter's inability to explain the behaviour of their algorithms is in itself sufficient to prove a lack of control, thus reckless use of technology. As an obvious consequence, therefore, corporate criminal liability will apply almost straightforwardly.

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Undeniably, the second scenario poses the greatest challenge for smooth and effective enforcement. In all such cases, we encounter an investment firm that, notwithstanding the observed manipulative conduct, claims to understand, control, and explain the market behaviour of its AI trading system. Furthermore, the firm may also assert that its trading strategy adheres to established market conduct rules. Proving intentional misconduct in this context would present a *probatio diabolica* for enforcement authorities, resulting in lengthy investigations that may even fail to ascertain liability. Such an outcome would leave victims uncompensated and expose markets integrity to the risks of AI trading manipulation. Given these circumstances, liability rules based on the legal concept of 'recklessness' rather than 'intent' offer a more suitable approach to safeguarding market integrity from those market actors who seek to externalise the costs of their malpractices to others. The adoption of a recklessness standard of liability would also align with the current legal treatment of other forms of market abuse such as insider trading, unlawful disclosure of inside information, and information-based manipulation.[798] Overall, it is posited that a recklessness standard of liability at the EU level would enable enforcement authorities to more effectively fight against forms of AI trading manipulation, hold accountable those individuals responsible for AI-enabled misconduct, and ultimately better ensure market integrity.

ii. Administrative liability

Criminal liability serves as crucial mechanism to enhance the credibility of deterrence against market manipulation by investment firms and their employees. Moreover, the establishment of a strong, smooth, and efficient regime of administrative sanctions holds the potential to ensure that investment firms undertake all requisite measures to operate within the legal boundaries of permitted conduct.

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798 *Cf*. Katja Langenbucher, 'Insider Trading in European Law' in Stephen M Bainbridge (ed), *Research Handbook on Insider Trading* (Edward Elgar Publishing 2013) 436-437; Chiara Mosca, 'Article 10: Unlawful Disclosure of Inside Information' in Marco Ventoruzzo and Sebastian Mock (eds), *Market Abuse Regulation: Commentary and Annotated Guide* (Oxford University Press 2017) 278-279; Marco Ventoruzzo, 'Comparing Insider Trading in the United States and in the European Union: History and Recent Developments' (2015) 11(4) European Company and Financial Law Review 554, 567 <https://doi.org/10.1515/ecfr-2014-0554> accessed 17 July 2024.

Generally, administrative sanctions can be designed to target both companies and individuals. Nevertheless, this dissertation contends that the establishment of a centralised mechanism, referred to as a 'single point of access', for regulatory litigation is desirable. A centralised enforcement regime against administrative violation might also be integrated with innovative policy tools such as AI personhood or other legal solutions,[799] including a 'risk management approach'[800] to liability. A single point of access to litigation is proposed to foster credible deterrence, thus effective enforcement. Furthermore, the proposed framework advocates for the implementation of a 'strict' liability rule for violations of the administrative prohibition on market manipulation.[801] With a 'single access point' for both enforcement authorities and plaintiffs, an EU-wide administrative sanction regime would expedite the sanctioning of offenders, also facilitating private litigation seeking the compensation of victims.

With a 'single access point' subject to 'strict' liability, investment firms may consider the desirability of mitigating their heightened risk exposure to sanctions by newly established insurance regimes specifically tailored for AI trading.[802] However, the feasibility of such insurance markets for AI systems relies on insurance companies' capability—but also business interest—to statistically evaluate risks associated with AI

799 According to some scholars, AI systems could also be legally conceived as corporate agents. *See, e.g.*, Anat Lior, 'AI Entities as AI Agents: Artificial Intelligence Liability and the AI Respondeat Superior Analogy' (2020) 46 Mitchell Hamline Law Review 1043, 1065–1075 <https://open.mitchellhamline.edu/mhlr/vol46/iss5/2> accessed 17 July 2024.

800 *See* Andrea Bertolini and Massimo Riccaboni, 'Grounding the Case for a European Approach to the Regulation of Automated Driving: The Technology-Selection Effect of Liability Rules' (2021) 51 European Journal of Law and Economics 243 <https://doi.org/10.1007/s10657-020-09671-5> accessed 17 July 2024.

801 For a discussion on the advantages of a 'strict' liability regime to regulate AI misconduct and harm, see Anat Lior, 'AI Strict Liability vis-à-vis AI Monopolization' (2020) 22 Columbia Science & Technology Law Review 90 <https://journals.library.columbia.edu/index.php/stlr/article/view/8055/4144> accessed 17 July 2024.

802 *Cf.* Gregory Scopino, *Algo Bots and the Law: Technology, Automation, and the Regulation of Futures and Other Derivatives* (Cambridge University Press 2020) 435–38; Abbott and Sarch (n 665) 382-383.

market manipulation and adequately price the corresponding premiums.[803] As an alternative solution, the concept of a 'compensation fund' for harm inflicted by AI trading manipulation could be contemplated. This option, however, requires careful policy consideration. In particular, it will be necessary to determine the precise mechanisms for financing such a fund, which could, for example, be supported by contributions from market participants themselves, as well as the criteria by which to guarantee victims access to compensation.[804]

Under both alternatives, investment firms would gain a more comprehensive understanding of the risks and limitations associated with potential liability for AI-enabled market manipulation from an *ex-ante* perspective. Meanwhile, the compensation of victims would be safeguarded from an *ex-post* viewpoint through the imposition of obligations on investment firms to pay damages, either through insurance premiums or contributions to the compensation fund. In either case, the proposed framework offers numerous advantages, primarily due to investment firms being the most suitable parties to minimise costs and risks arising from AI trading systems and potentially obtain AI insurance coverage.[805] Given the unintentional nature of certain forms of AI-enabled market manipulation, it may become necessary to establish a cap on the maximum fines and compensation.[806] One potential solution is to sanction investment firms by ordering the disgorgement of profits or losses

[803] *See* Michael Faure and Shu Li, 'Artificial Intelligence and (Compulsory) Insurance' (2022) 13(1) Journal of European Tort Law 1, 10-13 <https://doi.org/10.1515/jetl-2022-0001> accessed 17 July 2024.

[804] *See* Scopino (n 802) 439–443.

[805] *See* Bertolini and Riccaboni (n 800).

[806] *Cf., e.g.*, Barr and others (n 344) 23.

avoided,[807] thereby rendering operable one of the less frequently employed administrative powers available to NCAs.[808]

Moreover, trading venues should also bear liability when they neglect their legal obligations, under MiFID II, pertaining the governance of algorithmic trading on their electronic platforms. Therefore, in instances where enforcement authorities identify deficiencies on the part of trading venues in conjunction with investment employing a manipulative AI trading system, the former should be held accountable. In such circumstances, a liability rule based on 'contributory negligence' or 'recklessness' liability rule could be applied to ensure trading venues are held responsible for their omissions.[809] This approach would create stronger incentives for trading venues to diligently fulfil their delegated regulatory responsibility.

Overall, the proposed 'multi-layered' liability framework for AI trading manipulation is intended to generate numerous advantages. First, it aims to ensure that market actors engaging in malicious or reckless behaviour bear the costs of their AI trading misconduct. Simultaneously, this framework can guide technological innovation towards safer market applications that contribute to overall social welfare, without stifling innovation. Moreover, the enhanced liability regime proposed in this chapter is intended to facilitate the compensation of victims, incentivise investment firms to develop trustworthy AI trading systems, and foster a corporate culture that prioritises sound market conduct. Lastly, it enables more efficient and effective

[807] *Cf*. Hilyard Nichols, 'The First Byte Rule: A Proposal for Liability of Artificial Intelligence' (2023) SSRN preprint 1, 45-46 <https://ssrn.com/abstract=4446745> accessed 17 July 2024.

[808] *Cf*. MAR art 30(2)(b). For a discussion on the role of disgorgement of profits as an enforcement tool, see Vassilios D Tountopoulos, 'Market Abuse and Private Enforcement' (2014) 11(3) European Company and Financial Law Review 297 <https://doi.org/10.1515/ecfr-2014-0297> accessed 17 July 2024.

[809] *Cf*. Yadav (n 78) 1861-1866.

accountability and liability for those market participants who undermine the fair and orderly functioning of markets through their *pollutive* activities.[810]

6.6 Conclusion

In this chapter, we have addressed the issue of safeguarding the deterrence effect of market abuse regulations when confronted with AI-enabled market manipulation. Our focus was on analysing the effectiveness of the EU MAR/MAD regime's established liability rules and enforcement mechanisms in light of emerging challenges posed by ML-powered trading systems. Seven key techno-methodical attributes of ML-based trading were identified, namely: (i) 'automation and autonomy', (ii) 'complexity', (iii) 'correlation vs. causation', (iv) 'data dependency', (v) 'interconnectedness', (vi) 'opacity', and (vii) 'vulnerability'. Hence, we outlined the potential of ML-based systems to challenge traditional liability concepts, such as 'causation', 'foreseeability', negligence', and 'intent'.

Based on these findings, we then took a closer look at the implications of ML for the safe application of the liability rules established by legal prohibitions on market manipulation. In highlighting a number of significant uncertainties, we have found that the deterrence effect of the EU MAR/MAD regime might be substantially limited, thus leaving EU capital markets exposed to risks of rampant manipulation. Using Deterrence Theory as a normative framework, we revealed that achieving credible deterrence of AI market manipulation faces significant obstacles due to a number of factors, including (i) too vague legal prohibitions, (ii) ineffective liability rules, and (iii) inconsistent enforcement across Member States. Consequently, AI trading may be left operating within a quasi-lawless market environment.

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810 Here analogy is drawn with the so-called 'polluter-pays' principle related to ecological harm. *Cf.* Sanford E Gaines, 'The Polluter-Pays Principle: From Economic Equity to Environmental Ethos' (1991) 26(3) Texas International Law Journal 463 <https://heinonline.org/HOL/P?h=hein.journals/tilj26&i=473> accessed 17 July 2024.

Addressing these enforcement challenges necessitates a novel market conduct regulatory approach, advocating for reforms that align with the unique techno-methodical aspects of ML-powered trading. Therefore, this chapter articulates several policy recommendations. First, it emphasises the potential merits of an enhanced and 'harm-centric' definition of market manipulation, which can better take into account both ongoing evolution in market structure as well as technological advancements. Second, it urges the implementation of an improved and 'multi-layered' liability framework at the EU level in order to establish uniform enforcement.

All in all, these recommendations aim to bolster the legal framework, harmonise legal definitions, and strengthen enforcement regimes. All this can, in turn, foster deterrence, legal clarity, and effective regulation in order to preserve the integrity and stability of EU capital markets in the era of ML-powered trading.

7. THE SUPERVISION EU MARKET CONDUCT RULES: CHALLENGES AND FUTURE PERSPECTIVES

Following an analysis of the effectiveness of the EU enforcement regime in credibly deterring market manipulation by AI trading, in this chapter, we shift our focus to the implications for market conduct supervision. It should be noted that the enforcement and supervision of market conduct rules are two closely intertwined activities. The effectiveness of one closely depends on that of the other. Among the various activities of conduct supervision, market surveillance undoubtedly stands as a primary tool in the fight against market manipulation. Oversight of market conduct by monitoring trading activity in the markets enables financial supervisors to identify any suspicious behaviour, which can trigger investigations up to, in the case of established misconduct, lead to legal action. The presence and effectiveness of surveillance systems and mechanisms are therefore of paramount importance to enforcing the market conduct rules itself, as they help deter future misconduct.

Nevertheless, market conduct supervisors' ability to detect and investigate cases of algorithmic market manipulation may encounter several obstacles. These obstacles are mainly (i) legal in nature due to possible limitations of authority (e.g., the specific jurisdictional competence), and (ii) organisational, as supervisors do not always enjoy the resources, expertise, and technological equipment necessary to perform their tasks in an optimal way. Whenever supervisory activity is limited by one or more of these factors, it weakens effective law enforcement, making its deterrent effect less credible. As outlined in previous chapters, the potential for AI trading to optimise sophisticated forms of market manipulation and even engage in algorithmic collusion poses new challenges for financial authorities. These challenges also affect the effectiveness of existing supervisory frameworks in protecting market integrity in the EU. As the capabilities of AI trading continue to advance thanks to ML, algorithmic trading strategies become increasingly sophisticated, creating difficulties for the supervision of good market conduct. Supervisors must, therefore, keep pace with market and technological developments by strengthening their supervisory strategies and acquiring the expertise and technological capabilities needed to cope with the increasing sophistication of manipulative practices made possible by ML.

This chapter will explore the additional challenges AI trading poses to EU market conduct supervisors. As a first step, we will analyse the main factors that contribute to limiting financial supervisors' ability to detect and investigate the more sophisticated manipulative practices associated with ML-powered trading (Chapter 7.1). After these general remarks, we will take a closer look at the EU's approach to market conduct supervision in order to shed light on its limitations arising from shortcomings in the current supervisory architecture and strategy. This will then serve as a basis for discussing potential alternatives for improvement (Chapter 7.2). Among the ideas for achieving more effective supervision, we will then examine the potential offered by SupTech, particularly ML-based methods and tools, to address the new uncertainties introduced by market manipulation by AI trading (Chapter 7.3). Complementing proposals to strengthen the powers of EU supervisors, we will also discuss market-based solutions. In particular, we will contemplate the introduction of private enforcers as new supervisory actors, i.e. market manipulation' bounty hunters' (Chapter 7.4). Eventually, we will conclude with a summary of the main findings (Chapter 7.5).

7.1 General Causes of Failures in Market Conduct Supervision

To comprehend in full the growing difficulties for supervisors in combating market manipulation by AI trading, it is necessary to recall the intricate technological and structural aspects of the current market landscape, as discussed in the previous chapters.

Capital markets today are markedly dominated by trading algorithms. In these increasingly complex and highly dynamic market environments, which are characterised by high speed, interconnectivity, globalisation but also fragmentation. At the same time, there is a relentless quest for increasingly sophisticated trading strategies, thanks to ML methods, by the most innovative market players. Because of these factors, the task of financial supervisors becomes increasingly difficult. In particular, the identification of suspicious market conduct, according to existing legal definitions and established statistical methodologies, is limited. The difficulty in ensuring effective supervision is especially evident with certain ML-based trading strategies, due to their autonomy, opacity, and growing capabilities in terms of market presence and reach. More specifically, the obstacles presented by AI trading, due to ML, to ensuring effective supervision of market conduct are threefold.

First, AI trading not only challenge the ability of users to effectively control and monitor the trading activity of their systems and, thus, to comply with regulatory expectations, but also create significant 'information asymmetry' between regulated entities and financial supervisors. This is mainly due to the increasingly autonomous, complex, and sometime black box nature of specific ML applications. As discussed in Chapter 6, ML-based trading complicates the enforcement of market conduct rules. Even when financial supervisors may be able to detect some suspicious trading activities conducted by a given AI-powered trading system through market surveillance activities, they may find it difficult to accurately establish causation and ascertain the relevant mental state necessary for liability attribution and thus successful enforcement action.

Second, the optimisation capability of AI trading can render sophisticated forms of market manipulation increasingly difficult to be detected via traditional supervisory tools and methodologies. As AI trading substantially alters the spatio-temporal dynamics of market manipulation as an offence, it can often pass unnoticed under the supervisory radar. In particular, thanks to ML, trading algorithms can optimise the fast execution, modification, and cancellation of orders at high rates, making it challenging for financial supervisors to detect suspicious activity. Moreover, the sophistication of market manipulation as an economic phenomenon, due to ML, becomes increasingly hard to legally define and thus to regulate.

Third, effective market surveillance is also undermined by those sophisticated AI trading strategies that employ cross-asset, cross-market and/or cross-border techniques. Since their oversight activities are limited to supervising market conduct in domestic markets, supervisors may lack powers—let alone the technological equipment—to identify trading strategies that take place in multiple trading venues and across borders. After all, thanks to increasing market fragmentation coupled with not entirely harmonised regulation, malicious actors can structure and hide manipulative trading as part of complex strategies within highly networked markets.

In sum, owing to the technical specificities of ML-powered trading and the additional risks associated with it, several doubts arise about the ability of financial supervisors to police market conduct. In particular, the decentralised and fragmented structure of the institutional architecture of supervision is cause of limitations to the detection and prosecution of the most sophisticated forms of algorithmic market manipulation. But failures to detect market manipulation by AI trading can jeopardise market integrity, which in turn may put at risk financial stability. With these risks in mind, in the next section we offer an assessment of the ability of the EU supervisory framework to deal with the additional risks introduced by AI trading, due to ML.

7.2 Shortcomings in EU Market Conduct Supervision

Although recent reforms to EU capital markets law are intended to take into account developments in technology and trading practices, there are concerns about the adequacy of the current EU supervisory framework in addressing the additional risks introduced by AI trading.[811] More specifically, in assessing the effectiveness of the EU supervisory framework, which is organised along the 'three lines of defence' presented in Chapter 5, two main issues come to the fore.

First, the technical specificities of specific ML applications—particularly those based on complex methods such as DRL, which allow for the establishment of autonomous trading agents—can present a number of challenges for industry participants called upon to comply with regulatory requirements on the governance of algorithmic trading, particularly those on the control of market behaviour. Second, the widespread use of ML-based trading strategies, which are characterised by high speed, large volumes, and sophisticated activities, complicates trading monitoring tasks and in particular the ability of supervisors to detect suspicious cases of misconduct.

Based on these two general observations, in the following we will assess various causes of supervisory failure. Some of the biggest problems, however, seem to stem from the fact that the EU does not enjoy a cohesive approach to dealing with sophisticated forms of algorithmic market manipulation, especially when such practices span multiple markets and national borders. Moreover, EU financial supervisors tend to always find themselves at a technological disadvantage against private market participants. The uneven use of innovative technologies among players (i.e. investment firms) and game referees (i.e. financial supervisors) may challenge the latter's ability to ensure fair and orderly markets.

A. Sources of supervisory failure

In addition to their core regulatory responsibilities, market conduct authorities generally have a limited role in actively and continuously monitoring trading activity in their national markets. Actually, in supervising market conduct, NCAs rely heavily on close cooperation with the trading venues themselves, which provide alerts and

[811] *Cf*. MiFID II recitals (62) and (63).

information on potential violations, typically through the submission of STORs.[812] A careful assessment of the effectiveness of the current supervisory framework in dealing with AI trading reveals three main sources of concern. These include (i) the just-mentioned heavy reliance on cooperation from market operators, (ii) a lack of complete access to specific data related to algorithmic trading activities, and (iii) other inefficiencies due to the structure of market conduct supervision at the European level.

i. Reliance on the collaboration with trading venues

The high reliance on the close collaboration from trading venues in submitting STORs may not suffice to ensure effective market conduct supervision. Under this supervisory approach, supervisory actions are somewhat constrained by regulated entities' ability to effectively monitor trading on their platforms (i.e. trading venues) or under their trading codes (i.e. investment firms).[813] Both of these arrangements may not always guarantee that private firms have the right incentives to adequately police the market behaviour of market participants. On the one hand, trading monitoring systems necessitate considerable investments in technology and the acquisition of adequate expertise. On the other hand, trading venues may not always face the right incentives for effectively collaborating with supervisory authorities, as competitive pressures might force them to compromise market integrity for the sake of their own business interests.

Issues related to high reliance on the collaboration from trading venues are particularly relevant for those Member States where NCAs do not proactively engage in market surveillance activity. Conversely, these concerns may be less pronounced in those other jurisdictions where direct market surveillance is a crucial and more widely

812 *See* Yadav (n 78), discussing the supervisory architecture in the US; Busch (n 85) 79, discussing some of these issues from an EU perspective.

813 *See* discussion in Chapter 5.4.

employed tool in the arsenal of supervisors.[814] The case of The Netherlands, for instance, stands as an exemplar. In fact, not only the AFM conducts active market surveillance of national markets, but it is also actively involved in the exploration of cutting-edge technological application, such as ML-based methods and tools, to strengthen its supervisory arsenal.[815]

However, even when NCAs proactively engage with direct market surveillance, ensuring adequate market coverage and maintaining high-quality outcomes represents a significant challenge for supervisors. Specifically, absent a robust scientific methodology and appropriate technological equipment, detecting sophisticated forms of market manipulation can result being a daunting task for supervisory authorities.

ii. The problem of data availability

Another major problem is due to the lack of comprehensive access to trading data, particularly order book data, which prevents surveillance against some deceptive forms of manipulation. When confronted with 'order-based' market manipulation practices such as 'spoofing', which involves a rapid and frequent influx of order submissions, modifications and cancellations, market conduct authorities are limited by the manner in which the acquisition of data relevant to conducting investigations takes place.[816]

Unlike 'transaction data', in fact, which benefits from a fully harmonised reporting format and submission procedures, there is currently no legal framework or technical standards in place for the continuous transmission of 'order book data' from trading venues to NCAs.[817] This limitation, on the one hand, hampers the ability of

[814] *See* footnote n. 80.

[815] This information was learned by the author during a series of interviews held with staff at the Dutch AFM. *See also* footnote n. 345.

[816] *See* discussion in Chapter 5.4.

[817] *See* ESMA (n 309) 128-134.

NCAs to promptly obtain a complete and granular understanding of the trading activity taking place within their jurisdiction. On the other hand, it also undermines the ability of supervisors to coordinate and share information in a timely and efficient manner when they deal with cases with cross-border implications. Overall, adequate access to relevant supervisory data, such as order-based trading data, is a necessary component to ensure the effective market conduct supervision against those AI trading strategies that leverage fast interactions with market order books.

iii. Absence of cross-market supervision

The third main area of concern pertains more generally to the overall institutional structure of EU market conduct supervision. Specifically, the absence of a robust framework for conducting cross-market and cross-border supervision renders the existing supervisory architecture susceptible to oversight failures. Given the ability of certain AI trading strategies to optimise cross-market and cross-border forms of manipulation, thus, the current supervisory regime may expose EU capital markets to widespread instances of algorithmic market abuse. While trading monitoring activities are primarily conducted by trading venues on a single-market basis, these venues may not be optimally positioned for implementing effective cross-market surveillance.[818] Partly due to their primary focus on pursuing private business interests, trading venues may not always face the right incentives to allocate adequate resources towards contributing to the goal of market integrity from a more holistic perspective.

NCAs appear as the ideal candidate for conducting 'cross-market' surveillance,[819] as they have the potential, including the authority, to gain a more comprehensive perspective by aggregating data from various markets and trading venues. But still, data aggregation to be effective requires competent authorities to rely

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[818] *Cf.* Douglas Cumming and Sofia Johan, 'Global Market Surveillance' (2008) 10(2) American Law and Economic Review 454 <https://www.jstor.org/stable/42705539> accessed 17 July 2024.

[819] *See* ESMA (n 309) 128-134.

on the collaboration from industry players. However, since the current regulatory framework lacks provisions for real-time collection of relevant market data across EU market venues, this raises doubts about the capability of NCAs to achieve meaningful levels of cross-market surveillance without further improvements to the institutional architecture of EU market conduct supervision. It should be kept in mind, however, that any additional regulatory reporting requirements may likely result in increased compliance burdens for regulated entities. For this reason alone, any future reforms will need to carefully weigh the expected benefits and costs before they are implemented.

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The advancement of AI trading capabilities challenges both the enforcement and the supervision of market conduct rules. Malicious actors can take advantage of the optimisation capabilities of their AI systems to structure complex trading strategies that circumvent market surveillance mechanisms. In particular, complex forms of manipulation by AI trading can exploit the persistent lack of cross-market-and-border supervision of trading activity in EU markets. In light of this risk, the EU architecture of market conduct supervision needs to be strengthened—if not redesigned. One possible solution could involve further delegation of supervisory responsibilities at the supranational level, including greater and more direct involvement of ESMA in market surveillance. But greater centralisation of powers at the supranational level should be supported by an appropriate legal and institutional framework that addresses, among other things, the acquisition, storage, processing, and security of relevant supervisory data.[820] Part of the data governance issues are also recognised by ESMA itself, which in

[820] *See, e.g.*, Schmies and Sajnovits (n 623) 31-33, who discuss the challenges relating to the establishment of a European 'consolidated tape'; Andromachi Georgosouli and Jeremmy Okonjo, 'The Algorithmic Future of Insurance Supervision in the EU: A Reality Check', in Pierpaolo Marano and Kyriaki Noussia (eds), *The Governance of Insurance Undertakings: Corporate Law and Insurance Regulation* (Springer Cham 2022) 222-223 and 236-237 <https://doi.org/10.1007/978-3-030-85817-9_10> accessed 17 July 2024, who examines the incremental centralisation of powers on ESMA and highlights the trade-off between centralised and de-centralised supervisory data collection.

its data strategic plan for the coming years pledges to take a leading role as a central data hub to support the activity of all EU financial supervisors.[821] In what follows we discuss in more detail some of the most necessary steps to improve market conduct supervision at the EU level.

B. Strengthening the structure of EU market conduct supervision

The current supervisory architecture may result in part already outdated and, in any case, ill-equipped to deal with the additional risks to market integrity introduced by AI trading. It becomes apparent that the existing supervisory structure and strategies are better able to deal with older times' trading practices, characterised by a less fragmented market environment and less prevalence of algorithmic trading. Admittedly, the increasing sophistication of manipulation strategies due to ML, including forms that have cross-border and market implications, exceeds the capabilities of current supervisory frameworks, leaving EU markets exposed to fragility.

Given the supervisory deficiencies identified above, there are three possible areas for improvement that deserve further investigation, namely: (i) the establishment of effective cross-market and cross-border surveillance of trading activity, (ii) strengthening of supervisory data frameworks, and (iii) increased adoption of SupTech, enabling data-driven market conduct supervision leveraging cutting-edge ML-based technology.

i. Cross-market and cross-border surveillance

As previously argued, the EU lacks a fully integrated enforcement regime able to ensure credible deterrence against market manipulation. This unlevelled playing-field of the enforcement of market conduct rules creates opportunities for regulatory arbitrage

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821 ESMA, 'ESMA Data Strategy 2023-2028' (25 June 2023) ESMA50-157-3404, 8 <https://www.esma.europa.eu/sites/default/files/2023-06/ESMA50-157-3404_ESMA_Data_Strategy_2023-2028.pdf> accessed 17 July 2024.

that malicious actors can exploit to their own advantage. To address these risks, we also argued that greater harmonisation of Member States' national laws on market abuse is desirable.[822] At the same time, however, the EU also lacks a unified framework for the supervision of market conduct rules, which further contribute to render deterrence less credible.

Moving forward, some improvements to the current supervisory framework become necessary. First of all, there is a need to go beyond the single-market approach in market surveillance currently employed. In addition, the strong reliance on trading venues' collaboration in the monitoring of trading activity appears sub-optimal. However, the establishment of effective cross-market surveillance may require to re-think the very role of NCAs. Although being perhaps in the best position to conduct cross-market supervision of trading conduct, Member States' financial supervisors may ultimately face a number of challenges to ensure effective market surveillance. An effective cross-market surveillance framework would certainly require NCAs to have timely and extensive access to all relevant trading data from their domestic markets. Moreover, in addressing cases with cross-border implications, each NCA would also be required to achieve strong and smooth coordination with other financial supervisors.

There seems to be two main alternatives to achieve effective cross-market surveillance across various EU national markets. On the one hand, EU financial supervisors may need to rely on the greater involvement of market participants. To this end, new public-private partnership models on the development of SupTech and related applications—between NCAs, trading venues, and surveillance technology providers—may become desirable to ensure an efficient market conduct supervision.[823]

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[822] *See* discussion in Chapter 6.5.

[823] *Cf., e.g.*, Yueh-Ping (Alex) Yang and Cheng-Yun Tsang, 'RegTech and the New Era of Financial Regulators: Envisaging More Public-Private-Partnership Models of Financial Regulators' (2018) 21(2) University of Pennsylvania Journal of Business Law 354, 372-394 <https://scholarship.law.upenn.edu/jbl/vol21/iss2/3> accessed 17 July 2024, which discuss four different models to establish effective public-private partnership to enhance the technological

Alternatively, other innovative solutions may also emerge spontaneously from the market itself, as new market actors may find a business interest in the market surveillance industry, thereby shaping the competitive landscape in this space.[824] On the other hand, effective cross-market surveillance may require granting additional powers at the supranational level. Specifically, ESMA may become the leader authority within a newly established centralised architecture of EU market conduct supervision, thereby facilitating highest level of supervisory coordination among Member States.[825] Whether through increased coordination among NCAs, assisted by market actors within the supervisory landscape, or centralisation of market surveillance at the EU level, an effective cross-market surveillance framework will necessarily have to rely on an enhanced data framework that allow for real-time market conduct supervision and the adoption of cutting-edge technological solutions,[826] as outlined below.

ii. Centralised supervisory data platform

An improved supervisory data platform, enabling supervisors to access all relevant trading-related data for the effective surveillance of trading activity, is another key

capability of financial regulators, namely: (i) mixed-ownership RegTech organisation, (ii) contracted RegTech supporter, (iii) a quasi-public RegTech regulator, and (iv) directly delegated gatekeepers.

824 *See, e.g.*, Holly A Bell, 'Using the Market to Manage Proprietary Algorithmic Trading' in Hester Piece and Benjamin Klutsey (eds) *Reframing Financial Regulation: Enhancing Stability and Protecting Consumers* (Mercatus Center at George Mason University 2016) 266-268 <https://www.mercatus.org/media/62511/download> accessed 17 July 2024, highlighting the important role of cooperative market-based solutions in minimising competition between financial regulators and market participants on the development of market structure and oversight mechanisms.

825 *See, e.g.*, Karel Lanoo, 'MiFID II and the New Market Conduct Rules for Financial Intermediaries: Will Complexity Bring Transparency?' (2017) ECMI Policy Brief No. 24 <https://www.ceps.eu/ceps-publications/new-market-conduct-rules-financial-intermediaries-will-complexity-bring-transparency> accessed 17 July 2024.

826 *See, e.g.*, Arner, Barberis, and Buckley (n 765) 394-398, who discuss how the adoption of innovative technologies such as AI may enable to achieve a close to real-time and proportionate supervisory regime able, at the same time, to balance expected risks and efficient compliance.

element in creating a more integrated and comprehensive EU supervisory framework.[827]

Strengthening reporting arrangements can generally benefit the work of financial supervisors, as also envisioned by the European Commission in its strategy for supervisory data.[828] Ensuring that market conduct supervisors have access to all relevant data in a timely manner allows them to gain insights into the various trading strategies employed by market participants.[829] To achieve this improved supervisory capability, the establishment of a unified EU trading data platform seems desirable. With a common and integrated infrastructure for the collection and sharing of trading data, EU financial supervisors could better approximate real-time and cross-market surveillance of trading activity, as well as be facilitated in their coordination and information sharing necessary to tackle cross-border cases of manipulation.[830]

A good case in point of how the EU is equipping itself with common frameworks for managing relevant supervisory data is the European Commission's 2021 proposal to establish a European Single Access Point database for securities. Although this project is limited to specific categories of companies and types of financial data, it is still a step in the right direction.[831] More pertinently, it is the ongoing project to standardise the format of order book data and the development of mechanisms to facilitate the exchange of such data among various EU supervisors. As part of the development of an

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827 *Cf.* ESMA (n 821) 8-9.

828 *See* European Commission, 'Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Strategy on Supervisory Data in EU Financial Services' (12 December 2021) COM(2021) 798 final, 4-13.

829 *E.g.*, Fletcher (n 71) 542-543.

830 ESMA (n 821) 8-11.

831 *See* EU Commission, 'Proposal for a Regulation of the European Parliament and of the Council establishing a European single access point providing centralised access to publicly available information of relevance to financial services, capital markets and sustainability' (25 November 2021) COM/2021/723 final.

enhanced European data hub, in fact, European institutions are working on the creation of a platform dedicated to the collection and sharing of order book data.[832] The latter initiative should be greatly welcomed as it serves as a prerequisite for installing cross-border market surveillance, particularly for combating the more tedious forms of order manipulation.[833]

iii. Greater use of cutting-edge technology

In tackling sophisticated forms of market manipulation carried out by means of AI trading, EU financial supervisors face the more general challenge to equip themselves with adequate technology. As well known, public authorities typically find it hard to keep pace with private organisations in adopting cutting-edge technologies. In fact, they typically lag behind the private sector in terms of technological capabilities and related expertise.[834]

This limit is also recognised by the same ESMA, which is now putting efforts to modernise the arsenal of EU supervisors, by making available to them the necessary data, expertise, and tools to enable future-proof data-driven market conduct supervision.[835] To this end, ESMA also plans to serve as facilitator for the establishment of pilot projects and experimental environments allowing greater collaboration among NCAs as well as the development of joint expertise on the use of innovative technologies and their adoption in supervisory daily operations.[836] As will be explored in the next section in greater detail, the realm of SupTech can provide financial supervisors with advanced data analytics and automation tools to better conduct their

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832 *See, e.g.*, ESMA (n 821) 18.

833 *See, e.g.*, European Commission (n 832) recitals (69) and (70).

834 *See, e.g.*, Arner, Barberis, and Buckley (n 765) 397-398.

835 ESMA (n 821) 10.

836 Ibid 11.

supervisory tasks. In market conduct supervision, innovative technology such as AI, particularly ML, are intended to enable faster, more accurate, and efficient identification of market misconduct.[837]

7.3 'SupTech': Harnessing Technology to Enhance Supervision

Under the impulse of long-awaited regulatory requirements following recent policy reforms, such as MiFID II and MiFIR, industry players have been researching and adopting RegTech solutions to enhance their internal control, regulatory compliance, and risk management functions, among others.[838] By contrast, financial supervisors have generally lagged behind private organisations in the adoption of innovative technologies.[839] However, in parallel to the use of RegTech by industry participants, financial supervisors are becoming increasingly active in the research and experimentation of SupTech.[840] Somewhat specular to the concept of RegTech for regulated entities, the term SupTech broadly encompasses the adoption of cutting-

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837 *See, e.g.*, US Financial Industry Regulatory Authority (FINRA), 'Artificial Intelligence (AI) in the Securities Industry' (June 2020) 7 <https://www.finra.org/sites/default/files/2020-06/ai-report-061020.pdf> accessed 17 July 2024, reporting that the same regulated entities believe that cutting-edge technology offers the opportunity to move from "*traditional rule-based systems to a predictive, risk-based surveillance model that identifies and exploits patterns in data to inform decision-making*."

838 *See, e.g.*, Ross P Buckley and others, 'The Road to RegTech: The (Astonishing) Example of the European Union' (2020) 21 Journal of Banking and Regulation 26 <https://doi.org/10.1057/s41261-019-00104-1> accessed 17 July 2024.

839 *See* footnote n. 834; *see also* Pedro M Batista and Wolf-Georg Ringe, 'Dynamism in Financial Market Regulation: Harnessing Regulatory and Supervisory Technologies' (2021) 4(2) Stanford Journal of Blockchain Law & Policy 203, 205 <https://assets.pubpub.org/oj0iblwx/41625249371723.pdf> accessed 17 July 2024.

840 *See generally* Simone di Castri, Matt Grasser, and Arend Kulenkampff, 'Financial Authorities in the Era of Data Abundance: RegTech for Regulators and SupTech Solutions' (BFA, August 2018) <https://ssrn.com/abstract=3249283> accessed 17 July 2024; Simone di Castri and others, 'The Suptech Generations' (October 2019) BIS, FSI Insights on policy implementation No 19 <https://www.bis.org/fsi/publ/insights19.htm> accessed 17 July 2024; FSB, 'The Use of Supervisory and Regulatory Technology by Authorities and Regulated Institutions: Market Developments and Financial Stability Implications' (9 October 2020) <https://www.fsb.org/wp-content/uploads/P091020.pdf> accessed 17 July 2024; OECD, 'OECD Business and Finance Outlook 2021: AI in Business and Finance' (2021) 121-140 <https://read.oecd.org/10.1787/ba682899-en> accessed 17 July 2024.

edge technologies—such as AI, ML, Big Data analytics, etc.— by financial authorities to conduct supervisory activities and tasks in a more effective and efficient manner.[841]

In essence, SupTech presents the prospect of increased automation and streamlined administrative and operational procedures. It also involves the digitalisation of reporting and collection of regulatory data, thus enhancing the ability of financial regulators to analyse such data.[842] Furthermore, with continuous advancements in ML research, SupTech tools could play a role in guiding aspects of data management and analysis, and even support supervisory decision-making processes thanks to automation.[843]

In the context of our analysis, SupTech is generally proposed to augment market conduct supervision by allowing supervisory authorities their attention and resources on higher-value tasks that require human judgement.[844] Given the mounting difficulties associated with detecting and investigating sophisticated forms of market manipulation by AI trading, EU market conduct supervisors undoubtedly face strong incentives to upgrade their market surveillance methodologies and related

841 The term 'SupTech' can also encompass more broadly the use of technology by private organisations with some delegated supervisory responsibilities (i.e., trading venues, DEA providers, etc.). *See* Stefan Zeranski and Ibrahim E Sancak, 'Digitalization of Financial Supervision with Supervisory Technology (SupTech)' (2020) 8 Journal of International Banking Law and Regulation 309 <https://ssrn.com/abstract=3632053> accessed 17 July 2024.

842 *See, e.g.*, Dirk Broeder and Jeremy Prenio, 'Innovative Technology in Financial Supervision (Suptech) – The Experience of Early Users' (July 2018) BSI, FSI Insights on Policy Implementation No. 9 <https://www.bis.org/fsi/publ/insights9.pdf> accessed 17 July 2024.

843 *See, e.g.*, di Castri (n 840) 7.

844 *See, e.g.*, Bart van Liebergen, 'Machine Learning: A Revolution in Risk Management and Compliance?' (2017) 45 Journal of Financial Transformation 60, 66 <https://www.iif.com/portals/0/Files/private/32370132_van_liebergen_-_machine_learning_in_compliance_risk_management.pdf> accessed 17 July 2024; World Bank Group and Ministry of Foreign Affairs of the Netherlands, 'The Next Wave of Suptech Innovation: Suptech Solutions for Market Conduct Supervision' (*World Bank*, March 2021) <http://hdl.handle.net/10986/35322> accessed 17 July 2024, reporting several use cases of the adoption of SupTech solutions for market conduct supervision by various financial supervisory authorities around the world; *see also* FinCoNet, 'SupTech Tools for Market Conduct Supervisors' (November 2020) <https://www.finconet.org/FinCoNet-Report-SupTech-Tools_Final.pdf> accessed 17 July 2024.

technology.[845] In the following we explore some of the main benefits associated with AI-enabled market conduct supervision.

A. SupTech and market conduct supervision

Market conduct supervision represents a particularly promising application domain for SupTech for a good number of reasons. First of all, the high speed and enormous volume with which trading data is generated every day no longer allows regulators to rely solely on the manual work of their human experts in detecting and investigating market manipulation. In addition, humans, as opposed to automated systems, are susceptible to fatigue and cognitive biases, making them a costly and sometime not entirely reliable resource.[846]

By leveraging SupTech tools, hence, supervisors can more accurately and objectively analyse trading activity in near real-time, leading to improved supervisory outcomes. Although the support of ML-based analysis tools enables more effective identification of suspicious trading activities, it should still be noted that the human factor is not entirely eliminated. Every suspicious activity report generated by surveillance systems always requires further investigation by human analysts, who still remain an integral part of the process (i.e. so-called ‘human in the loop' approach).[847]

Overall, AI-powered market conduct supervision can enable supervisors to gain a more comprehensive and granular perspective of trading activity, giving them the ability to take a more proactive and predictive approach to market surveillance. Thanks

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845 *Cf.* ESMA (n 821) 10-12.

846 *See, e.g.*, Marcus Buckmann, Andy Haldane, and Anne-Caroline Hüser, ‘Comparing Minds and Machines: Implications for Financial Stability' (2021) 37(3) Oxford Review of Economic Policy 479, 485-486 <https://doi.org/10.1093/oxrep/grab017> accessed 17 July 2024.

847 Partly, this is also because the mere use of AI systems in market surveillance does not eliminate the possible occurrence of biased or erroneous outcomes. *See generally* Nir Kshetri, ‘Regulatory Technology and Supervisory Technology: Current Status, Facilitators, and Barriers' (2023) 56(1) Computer 64, 70-71 <https://doi.ieeecomputersociety.org/10.1109/MC.2022.3205780> accessed 17 July 2024.

to SupTech applications, particularly those based on ML methods, financial supervisors have today the opportunity to narrow the technology gap that has long separated them from industry participants. In the following we will explore both opportunities and challenges relating to the adoption of SupTech tools by EU market conduct authorities.

B. AI-powered market surveillance

The use of AI tools in market surveillance is by no means a new development introduced by the latest wave of innovations in the field of SupTech.[848] The real novelty lies in the integration of innovative ML methods in supervisory methodologies and practices. But despite the potential offered by SupTech solutions, the extent to which financial supervisors engage with these innovative technologies varies widely across jurisdictions. While some authorities research and develop market surveillance systems in-house, others acquire such tools from third-party providers or, if they are not actively engaged in direct market surveillance, simply rely on the assistance provided by private supervisory bodies, such as trading venues.[849]

i. An introduction to market surveillance systems

Market surveillance systems typically integrate computational decision support systems with communication and visualisation tools, as well as other facilities.[850] As main objective, market surveillance activity aims to identify unusual patterns in trading data, usually referred to as 'suspicious' trading activity. This can be accomplished by

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848 For an introduction to different generations of AI in market surveillance, see Mohd Asyraf Zulkifley and others, 'Stock Market Manipulation Detection Using Artificial Intelligence: A Concise Review' in *2021 International Conference on Decision Aid Sciences and Application (DASA)* (IEEE 2022) 165-169, <https://doi.org/10.1109/DASA53625.2021.9682322> accessed 17 July 2024.

849 *Cf*. FSB (n 840) 14-15.

850 *See* Peter Goldschmidt, 'Compliance Monitoring in a Complex Environment: An Overview' in Guy G Gable and Ron AG Weber (eds), *PACIS '97: Proceedings of the 3rd Pacific Asia Conference on Information Systems: "The Confluence of Theory and Practice"* (Information Systems Management Research Concentration, Queensland University of Technology 1997) 554 <https://aisel.aisnet.org/pacis1997/53> accessed 17 July 2024.

analysing anomalies in trading patterns or identifying outliers among observed market behaviours.[851]

Currently, the prevailing approach employs 'indicator-based' surveillance methods to analyse trading activities and spot unusual patterns. These indicators are generally calculated with reference to market prices or volumes, strategy profitability, or any other relevant indicator. In addition, 'unusual' patterns are typically defined based on the enforcement experience of human supervisors and are commonly implemented through 'rule-based' methods or other statistics-based approaches.[852]

As an outcome of the monitoring activity, surveillance systems generate red alerts whenever a suspicious trading observation or pattern is detected, which, however, requires further examination by human analysts.[853] To implement reliable surveillance systems, however, human analysts need to establish predetermined (statistical) tolerance levels, above which to assess trading activity deemed 'suspicious'. Regardless of the specific AI tools and underlying statistical methods employed, any application of surveillance systems is somewhat susceptible to false positive and false negative problems at any given tolerance level. Even more advanced analytical models based on ML may encounter a variety of challenges when confronted with the statistical properties of highly complex domains, such as capital markets.[854] As a consequence,

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851 From a statistical point of view, the analysis of 'anomalous' market behaviour presents a number of methodical challenges. For a discussion of some of these challenges in the context of the detection of insider trading, see Piero Mazzarisi and others, 'A Machine Learning Approach to Support Decision in Insider Trading Detection' (2022) Quaderni FinTech No. 11, Consob, Dicembre 2022, 1-3 <https://www.consob.it/documents/1912911/1933915/FinTech_11.pdf/eebb010d-e5e8-9f75-9e77-b2a1407e418f> accessed 17 July 2024.

852 *E.g.*, Xin Li and others, 'Design Theory for Market Surveillance Systems' (2015) 32(2) Journal of Management Information Systems 278, 281 <https://doi.org/10.1080/07421222.2015.1063312> accessed 17 July 2024.

853 *See* Abbas Bagherian Kasgari, Mohammad Taghi Taghavifard, and Saeideh Golchin Kharazi, 'Price Manipulation Fraud Detection by Intelligent Visual Fraud Surveillance System' in *6th International Conference on Control, Decision and Information Technologies (CoDIT)* (IEEE 2019) 1646, 1647 with further reference <https://ieeexplore.ieee.org/document/8820499> accessed 17 July 2024.

854 *Cf.* Goldschmidt (n 850) 556.

the cost incurred by human supervisors in reviewing computer-generated alerts and outcomes can vary depending on specific temporal and contextual characters of the additional information required to evaluate a suspected case of market manipulation and determine its acceptance or rejection.[855]

Overall, while human judgement remains an essential and fundamental component of market conduct supervision, advanced technology can complement the work of human analysts by aiding the identification of anomalies and the accumulation of corroborating evidence. In what follows we explore how continuous progress in ML research offers today the opportunity to supervisors to explore increasingly powerful market surveillance systems.

ii. From rule-based to ML-based market surveillance systems

In current market surveillance systems, the dominant computational techniques consist mainly of more conventional AI approaches, such as 'rule-based' systems. However, despite their prevalence, these methods are quite rudimentary and are not always entirely accurate. Their main drawback lies in their heavy reliance on the domain-specific knowledge of the human experts on which they are based. Being susceptible to false-positive and false-negative results, these systems often fail to detect the more subtle and sophisticated manipulation strategies employed by market participants.[856]

Regardless of the specific method employed, the operationalisation of market surveillance generally presents a number of methodical challenges for financial supervisors:

[855] Goldschmidt (n 850) 555-557 with further reference.

[856] *See, e.g.*, Zulkifley and others (n 848) 165.

(i) the identification of 'unusual' agents is usually a daunting task, as they are initially unknown and must be discovered based on available data;

(ii) the definition of patterns of unusual behaviour is inherently subjective and, as such, may vary among different users, the analysis and in any case may evolve over time; and

(iii) the vast amount of data to be analysed places a significant burden on human experts and necessitates adequate data validation processes.[857]

To overcome some of these limitations, ML methods are today proposed as a means to empower financial supervisors in monitoring market behaviour and outcomes through innovative and data-intensive applications. Various ML methods can be employed in the detection of market manipulation, including conducting prediction or classification tasks (i.e. supervised learning),[858] as well as clustering tasks (i.e. unsupervised learning).[859] Most advanced surveillance systems may also make use

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857 *Cf.* Goldschmidt (n 850) 555 with further reference.

858 *See, e.g.*, Koosha Golmohammadi, Osmar R Zaiane, and David Díaz, 'Detecting Stock Market Manipulation using Supervised Learning Algorithms' in Longbing Cao and others (eds), *2014 International Conference on Data Science and Advanced Analytics (DSAA)* (IEEE 2014) 435 <https://ieeexplore.ieee.org/abstract/document/7058109> accessed 17 July 2024, proposing a supervised learning algorithm to support the identification of market manipulation; Nurullah Celal Uslu and Fuat Akal, 'A Machine Learning Approach to Detection of Fraud-Based Manipulations in Borsa Istanbul' (2022) 60 Computational Economics 25 <https://doi.org/10.1007/s10614-021-10131-8> accessed 17 July 2024, proposing a supervised learning classification model to detect trade-based manipulation from daily data.

859 *See, e.g.*, Jia Zhai and others, 'Coarse and Fine Identification of Collusive Clique in Financial Market' (2017) 69 Expert System with Applications 225 <https://doi.org/10.1016/j.eswa.2016.10.051> accessed 17 July 2024, proposing an unsupervised learning model to examine the characteristics of collusive trading and support their detection; Baqar Abbas, Ammar Belatreche, and Ahmed Bouridane, 'Stock Price Manipulation Detection Using Empirical Mode Decomposition Based Kernel Density Estimation Clustering Method' in Kohei Arai, Supriya Kapoor, and Rahul Bhatia (eds), *Intelligent Systems and Applications. IntelliSys 2018. Advances in Intelligent Systems and Computing, vol 869* (Springer Cham 2018) 851-866 <https://link.springer.com/chapter/10.1007/978-3-030-01057-7_63> accessed 17 July 2024, proposing an unsupervised learning model for detecting market manipulation in HFT markets.

of DL methods, which allow to research powerful analytical tools able to uncover meaningful patterns of both old and new manipulative strategies.[860] The latter approaches, however, require more than others that human users take all precautionary steps—with regard to, for instance, definition of market manipulation and relate misclassification problems, data validity and accuracy, model selection, interpretability of results, etc.—to ensure safe and reliable applications. This is mainly because DL methods can exacerbate the explainability problems of alerts or recommendations generated by these systems.[861]

In sum, it is undeniable that equipping market conduct supervisors with powerful analytical tools has become imperative in combating the escalating sophistication of manipulative practices. Indeed, distinguishing the market effects resulting from AI-optimised forms market manipulation from other legitimate behaviours is increasingly challenging. However, ML-based surveillance tools may help relax some of these constraints, enabling human supervisors to dispose of increasingly powerful analytical methods. With advanced ML methods, not only can the human analyst better identify anomalous trading activity, but also be able to predict potential manipulative behaviour by future manipulators based on their previously observed conduct.[862] As will discussed in the next section, a new wave of powerful market surveillance approaches is emerging thanks to the combination of ML, particularly RL, with 'Agent-Based Modelling' (ABM) methods. These advanced approaches own the promise to enable financial supervisors to develop a behavioural-based science to

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860 For a review of DL-based approaches to market surveillance, see Mohd Asyraf Zulkifley and others, 'A Survey on Stock Market Manipulation Detectors Using Artificial Intelligence' (2023) 75(2) Computers, Materials & Continua 4395 <https://doi.org/10.32604/cmc.2023.036094> accessed 17 July 2024.

861 *Cf.* Samira Khodabandehlou and Seyyed Alireza Hashemi Golpayegani, 'Market Manipulation detection: A Systematic Literature Review' (2022) 210 Expert Systems with Applications, Article 118330, 11-16 <https://doi-org.libproxy1.nus.edu.sg/10.1016/j.eswa.2022.118330> accessed 17 July 2024.

862 *Cf.* Coglianese and Lai (n 397).

better understand, thus regulate, the intricate mechanics underlying the most sophisticated forms of algorithmic market manipulation.[863]

C. The integration of ML and 'Agent-Based Modelling' methods

'Agent-Based Modelling' (ABM) encompasses a set of computational methods, which allow to explore the properties of complex systems by simulating the actions and interactions of its individual agents. ABM-based methods require a number of basic steps. Specifically, human experts must identify, model, and programme three essential elements:

(i) a collection of 'agents', their behaviour, along with the goals associated with them;

(ii) the 'relationships' that govern the interactions between these agents; and

(iii) the 'environment' within which these agents operate.[864]

Within the context of our analysis, ABM provides a valuable tool for building multi-agent systems that simulate the market behaviour of algorithmic traders, their interactions, and the resulting effects on markets. ABM thus facilitates the analysis of specific algorithmic trading strategies and their impact on, for instance, market integrity. Insights provided by simulations can be used as a starting point for evaluating the effectiveness of existing market rules and alternatives to them.[865] However, it should be noted that ABM methods rely on certain fundamental assumptions to

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863 *See, e.g.*, Cartea and others (n 345); Barr and others (n 344).

864 For an introduction to ABM methods, see Charles M Macal and Michael J North, 'Tutorial on Agent-Based Modelling and Simulation' (2010) 4(3) Journal of Simulation 151 <https://doi.org/10.1057/jos.2010.3> accessed 17 July 2024.

865 For a survey on ABM methods applied to the study of algorithmic agents' behaviour and their implication for market quality, see Takanobu Mizuta, 'A Brief Review of Recent Artificial Market Simulation (Agent-Based Model, ABM) Studies for Financial Market Regulations and/or Rules' (2023) SSRN preprint 1 <https://mizutatakanobu.com/SSRN-id2710495.pdf> accessed 17 July 2024.

encapsulate certain beliefs about agent behaviour, namely, they essentially build upon a behavioural theory that describes how agents act in a given environment.[866]

The integration of ML with ABM allows the synergetic capabilities of the two methods to be exploited in a single application.[867] More traditional ABM approaches, hence non-ML, typically require explicit *ex-ante* programming of agent behaviour by human experts and thus rely on strong model assumptions. Instead, the use of ML methods in ABM allows the inference of behavioural rules of trading agents based on empirical data, which human experts can then test in various scenarios. These methods also make it possible to study the trading behaviour of adaptive agents that can respond to changing market conditions, including the rules governing their interactions.[868]

In principle, various ML methods can be integrated into ABM to model the dynamics of complex environments such as capital markets. These methods are generally proposed to improve model accuracy and, as such, they can provide valuable insights to support decision-making tasks by human experts.[869] It is important to note that RL methods—which, as discussed in Chapter 22.3, constitute a foundational ML paradigm for researching autonomous artificial traders[870]—can assist financial regulators study and better understand the (mis-)behaviour of various market agents through simulation and observation of their trading activity and the resulting market effects. Crucially, these methods also enable reverse engineering of the inner workings

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866 *Cf.* Blake Lebaron, 'Chapter 24: Agent-Based Computational Finance' in Leigh Tesfatsion and Kenneth L Judd (eds), *Handbook of Computational Economics, Vol. 2* (Elsevier 2006) 1187-1233 <https://doi.org/10.1016/S1574-0021(05)02024-1> accessed 17 July 2024.

867 *See* Wie Zhang, Andrea Valencia, and Ni-Bin Chang, 'Synergic Integration Between Machine Learning and Agent-Based Modeling: A Multidisciplinary Review' (2021) 34(5) IEEE Transactions on Neural Networks and Learning Systems 2170 <https://doi.org/10.1109/tnnls.2021.3106777> accessed 17 July 2024.

868 *See* ibid 2170-2171; Cartea and others (n 345).

869 *See* Zhang, Valencia, and Chang (n 867) 2174, contextualising this claim with some illustrative examples.

870 *See* Chapter 2.3.C.

of RL-based agents (i.e. 'inverse RL') by allowing the human analyst to gain insights into the trading behaviour of these agents.[871]

Undoubtedly, the integration of ML methods with ABM represents an exciting advance in financial market science, potentially finding great scope in the practice of market surveillance. Actually, the most innovative supervisory authorities are actively exploring these methods to better understand the dynamics and effects of specific forms of algorithmic market manipulation, which are otherwise notoriously complicated to analyse and even to define precisely.[872] While these innovative methods present great opportunities for financial regulators in improving their regulatory science, their effective implementation also requires addressing certain practical and methodical challenges, as discussed below.

i. Opportunities and challenges

ABM-based methods offer the opportunity for financial regulators to aspire to bolster their capacity to effectively detect, analyse, and address complex market behaviours, including sophisticated forms of market manipulation. These methods indeed provide regulators with improved behavioural-based scientific knowledge about capital markets.

Assuming the availability of relevant data of the utmost quality—e.g., representative of market manipulation—ABM can provide financial supervisors with fundamental insights into the nature and mechanics of specific forms of manipulation. This knowledge can serve two primary purposes. First, it can act as a theoretical

[871] *See* ibid 2178-2179. Various RL approaches have been proposed to study the market behaviour of algorithmic trading agents. *See, e.g.*, Shearer, Rauterberg, and Wellman (n 344); Cartea and others (n 345); Barr and others (n 344); Byrd (n 344).

[872] This is what emerged from interviews by the author with Dutch AFM staff. In particular, the AFM has initiated a project in collaboration with The Alan Turing Institute to apply ABM techniques to the study of economic mechanics and the market effects of sophisticated market manipulation strategies such as spoofing. *See also* Cartea and others (n 345).

framework to facilitate the legal definition and regulation of sophisticated forms of market manipulation that are usually hard to comprehend and clearly distinguish from other trading strategies. As a result, this also benefits the supervision and enforcement of market conduct rules, as regulators can rely on a more robust understanding of these practices. Second, perhaps more interestingly, these methods can open up new perspectives as entirely new regulatory tools for algorithmic trading behaviour. In particular, as ABM-based analysis enables learning about the mechanics of algorithmic manipulative behaviours, this knowledge can then be used for algorithmic auditing purposes. The specific domain knowledge learned about various forms of market manipulation and their effects on markets, including the behaviour of other agents, can also serve another fundamental purpose. It can be used as a benchmark for testing trading algorithms before their actual implementation in markets. Therefore, ABM-based methods can serve as a novel *ex-ante* regulatory tool, ultimately enabling the establishment of a well-formalised certification regime for trading algorithms against pre-defined 'good market conduct' standards that align with regulatory expectations.[873] Moreover, recent research shows ABM-based analysis can also allow financial regulators to understand how specific algorithmic trading strategies may be able to obfuscate their malicious trading behaviours, by resembling some normal trading conditions, in order to evade detection by market surveillance systems.[874] This knowledge could therefore be used to fine-tune surveillance systems to address the increasingly sophisticated character of market manipulation as an offence.

Once a reliable simulation environment for algorithmic market behaviour is in place, financial regulators may also employ it for other regulatory purposes. Specifically, this regulatory framework could also be open sourced to industry

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873 *See* footnote n. 872.

874 *Cf.* Xintong Wang and Michael P Wellman, 'Market Manipulation: An Adversarial Learning Framework for Detection and Evasion' in Christian Bessiere (ed), *IJCAI'20: Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence* (International Joint Conferences on Artificial Intelligence 2020) 4626-4632, <https://www.ijcai.org/proceedings/2020/0638.pdf> accessed 17 July 2024.

participants, enabling them to use it for the behavioural testing of their algorithmic trading systems and strategies. This would serve as a less ambiguous framework, as compared to existing ones, for the internal auditing of trading algorithms. Ideally, however, the development of such a framework should result from a collaborative effort among multiple stakeholders, including financial regulators and regulated entities, which together can work to establish precise standards and measures to define specific forms of market manipulation from both an economic and legal perspective.[875] Among other things, such a multi-stakeholder collaboration would involve the definition of the cause-effect elements necessary to configure complex instances of algorithmic market manipulation as violations of market conduct rules. This, for instance, would allow to determine what factual evidence is necessary to unequivocally classify, on a commonly agreed basis, what constitutes a deceptive market trading activity for the purpose of regulating legitimate market conduct. However, it is also important to acknowledge that a testing framework of this nature may inadvertently create opportunities for market players to exploiting increased regulatory transparency with regard to the definition of market manipulation from a behavioural perspective. In fact, as regulated entities may always be seeking to adapt to regulation strategically, they could find new ways to circumvent market rules for their own private business interest.[876]

Nevertheless, there are also some fundamental challenges that financial regulators need to face for the safe and reliable implementation of ABM-based methods. A first notable challenge lies in the complexity of modelling some sophisticated forms of market manipulation, such as spoofing, that are known to confuse financial regulators. This challenge usually arises due to the inherent difficulty

875 This is what emerged from the author's interviews with Dutch AFM staff.

876 *E.g.*, Hilary J Allen, 'Experimental Strategies for Regulating Fintech' (2020) 3(1) Journal of Law and Innovation 1, 5-6 <https://scholarship.law.upenn.edu/jli/vol3/iss1/1> accessed 17 July 2024, arguing that technological innovation may provide more opportunities for regulated entities to exploit regulatory arbitrage.

of distinguishing the actual business motives of these manipulation strategies from legitimate trading activities (e.g., market making). Indeed, discerning the true intentions behind market manipulation, such as spoofing, can be difficult, particularly in determining whether legitimate or illicit economic factors drove a particular trading decision. Although simulations of market behaviour through ABM methods can help generate insights into the market effects of specific trading patterns, human experts must nevertheless test the knowledge gained through these methods in order to rely on them. As part of ensuring the validity of these methods, public authorities also need to carefully balance issues of transparency and accountability when incorporating ML-based ABM in their supervisory methodologies. Within the EU, for instance, administrative agencies such as financial regulators are bound to fulfil their institutional mandates while ensuring compliance with EU fundamental values and principles. The latter include, for instance, the principle of good administration[877] and other legal safeguards[878].[879] Therefore, addressing issues of explainability throughout the entire AI lifecycle becomes imperative, as highlighted in the existing body of scientific literature.[880] Among other things, this requires adopting an engineering

[877] *See* Charter of Fundamental Rights of the European Union of 26 October 2012, 2012/C 326/02 [2012] OJ C 326/391 [hereinafter CFR] art 41 and relevant case law. The 'right of good administration' is a multi-faceted legal concept encompassing the 'right to have affairs handled impartially, fairly and within a reasonable time', as well as the 'right to be heard', the 'right to have access to file', the 'administration's obligation to give reasons for its decision', and the 'right to be compensated for damages'. It also underpins the 'right of defence' of persons whose legal position may be adversely affected by the legal effects of a measure taken by EU administrations.

[878] These other legal safeguards include, for instance, the 'right to respect for private life' (CFR art 7) and, whenever administrative sanctions have a criminal nature, additional legal protections also apply, such as the 'right not to incriminate oneself' (CFR art 48).

[879] *See generally* Jane Reichel, 'Ensuring the Principle of Good Administration in the EU Financial Market Law' in Carl Fredrik Bergström and Magnus Strand (eds), *Legal Accountability in EU Markets for Financial Instruments: The Dual Role of Investment Firms* (Oxford University Press 2021) 126 <https://doi.org/10.1093/oso/9780192849281.003.0006> accessed 17 July 2024.

[880] *See* Alessio Azzutti, Pedro M Batista and Wolf-Georg Ringe, 'Good Administration in AI-enhanced Banking Supervision: A Risk-based Approach' (2023) European Banking Institute Working Paper Series 2023 – no. 140 <https://ssrn.com/abstract=4430642> accessed 17 July 2024, examining the legal implications of AI deployment in EU banking supervision and proposing a risk-based regulatory framework that addresses governance aspects across the entire AI lifecycle.

approach towards explainability to uphold these principles and meet legal obligations.[881]

Moreover, as a common problem in ML, access to high-quality data is critical to ensure safe and reliable applications. In principle, ABM-based methods can work on both empirical and synthetic data. Yet, financial supervisors may sometimes face significant hurdles in acquiring sufficient data samples representative of market manipulation in order to train their market surveillance systems. On the one hand, data scarcity is due to the lack of quality and accessibility of 'order book data', which is internally stored by market participants. On the other hand, financial supervisors may lack substantial samples of past observations of market manipulation, given the inherent difficulty in identifying certain order-based forms of manipulation, such as spoofing. While empirical data should always be preferred, they can be augmented when they are insufficient in volume. However, it is essential to acknowledge that using synthetic data entails making strong assumptions about their statistical properties, and, as such, they may fail to represent reality accurately.[882]

Despite the above-mentioned practical and methodical challenges, the integration of ML and ABM offer today exciting tools to enhance the regulatory science of financial regulators. In what follows we will try to demonstrate the usefulness of these innovative methods in regulating complex forms of market manipulation, using spoofing as a case study.

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881 *Cf.* De Silva and Alahakoon (n 243).

882 *See, e.g.*, James B Heaton and Jan H Witte, 'Synthetic Financial Data: An Application to Regulatory Compliance for Broker-Dealers' (2019) 50 Journal of Financial Transformation 32 <https://www.capco.com/Capco-Institute/Journal-50-Data-Analytics/Synthetic-Financial-Data-An-Application-To-Regulatory-Compliance-For-Broker-Dealers> accessed 17 July 2024.

ii. ABM as a regulatory tool: The case of 'spoofing'

As is well known, sophisticated forms of market manipulation such as spoofing are very difficult to define.[883] Through years of enforcement, however, financial supervisors have identified certain trading patterns that they consider indicative of spoofing. Although these patterns may serve as a basis for initiating investigations into suspicious market conduct, they do not in themselves provide an exact definition of market manipulation and, as such, do not constitute sufficient evidence of misconduct.[884] Hence, additional evidence and the judgment of human experts are needed to determine violations, as these manipulative practices often closely resemble legitimate trading activities.

In this context, ML-powered ABM analysis can serve as a valuable tool to help financial supervisors achieve more accurate results. Thanks to these methods, supervisors can develop a deeper understanding of the behavioural aspects underlying such complex forms of market manipulation.[885] In particular, ABM-based methods enable the investigation of those market settings where a 'spoofer' can successfully profit. These methods also allow for the quantification of the effects of 'spoofing' strategies on the behaviour of other market participants and overall market quality.[886] But for the modelling of 'order-based' forms of manipulation to be effective, both

[883] *See, e.g.*, Álvaro Cartea, Sebastian Jaimungal, and Yixuan Wang, 'Spoofing and Price Manipulation in Order Driven Markets' (2020) 27(1-2) Applied Mathematical Finance 67 <https://doi.org/10.1080/1350486X.2020.1726783> accessed 17 July 2024.

[884] *See* Collin Starkweather and Izzy Nelken, 'Behind the Curtain: The Role of Explainable AI in Securities Markets' (31 July 2020) Securities Regulation Daily, Wolters Kluwer, 7 <https://www.supercc.com/pdf/Behind-the-Curtain_07-31-2020.pdf> accessed 17 July 2024.

[885] *See, e.g.*, Stewe Yang and others, 'Behaviour Based Learning in Identifying High Frequency Trading' in *2012 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)* (IEEE 2012) 1-8 <https://doi.org/10.1109/CIFEr.2012.6327783> accessed 17 July 2024, addressing the techno-methodical challenges of modelling algorithmic trading strategies, such as "spoofing", through inverse RL methods.

[886] *See* Xintong Wang, Christopher Hoang, Yevgeniy Vorobeychik, and Michael P Wellman, 'Spoofing the Limit Order Book: A Strategic Agent-Based Analysis' (2021) 12(2) Games, Article 46 <https://doi.org/10.3390/g12020046> accessed 17 July 2024.

transaction and order book data must be available. Without both of these categories of data, it is virtually impossible to determine which agents have initiated a specific spoofing attack. This is because these types of strategies rely on deceptive tactics involving high rates of sending and cancelling orders to attract other traders to trade in the direction desired by the manipulator.

Assuming the availability of relevant data, adopting a behaviour-based approach enables financial regulators to improve their ability to delineate precise boundaries between algorithmic behaviours that exhibit manipulative tendencies and those that do not. This, in turn, allows regulators to have a more robust and scientifically based framework for investigating alleged cases of market manipulation. As extensively discussed above, for sophisticated forms of manipulation such as 'spoofing', establishing intent or any other relevant mental state as a basis for liability can be challenging for enforcement bodies. Nevertheless, financial supervisors can still infer some form of *scienter* by evaluating whether a specific trading decision or pattern has had an unnatural impact on the trading behaviour of other market participants. That basically constitutes an effect-based assessment.[887] The latter, though, must be based on a sound and well-established methodology allowing to analyse the effects of deceptive market behaviours. In the end, this exercise represents a causality assessment. Relatedly, merely demonstrating the ability of an agent to influence and alter the behaviour of other market participants is in itself insufficient to establish causation. For conduct to be classified as a crime, in fact, there must be an underlying intent to deceive other agents in order to profit.[888] But proving such intent can often be arduous, especially in the case of ML-based autonomous and black box trading systems.[889]

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[887] *E.g.*, ibid; Barr and others (n 344); Cartea and others (n 345).

[888] *See* discussion in Chapter 5.2.

[889] *See* discussion in Chapters 6.2-6.3.

Consider, for instance, the scenario of RL-based trading agents. As we have previously observed, these agents, in pursuit of predetermined goals, may become capable of independently discovering highly profitable strategies while ignoring market conduct rules, regardless of human intent. As these methods can be opaque even to their own users, supervisory authorities face mounting difficulties in auditing RL-based algorithmic trading and their market behaviour. However, through ABM-based simulations and analysis, financial regulators could better understand the implications of RL-based agents and their trading strategies on the quality and integrity of markets. As an example, if it turns out to be possible to demonstrate that a particular strategy is put in place to deceive other traders and, on average, allows its executor to make a profit or extra-return then this could serve as a basis for assigning liability. If then, because questioned about such conduct, the responsible investment firms are unable to credibly explain why their algorithms behaved as they did, that could be sufficient to give rise, at a minimum, to administrative liability for misconduct.[890]

The foregoing analysis, even if only from a conceptual standpoint, demonstrates the benefits to financial regulators of developing a behavioural approach to the study of market manipulation. In this regard, ML-based ABM methods could be increasingly leveraged in the future as part of a broader strategic vision to adopt innovative SupTech solutions. In the following, however, we explore some of the main challenges that EU financial regulators and supervisors may face in moving towards an EU-wide SupTech ecosystem.

D. Organisational, legal, and reputational challenges

Given the growing complexities to ensure market integrity, market conduct supervisors need enhanced strategies and more reliable tools to effectively detect market manipulation. In this context, the adoption of SupTech holds the potential to greatly benefit the daily operations of financial supervisors along various dimensions. Most

[890] *Cf.* discussion in Chapter 6.5.B.

notably, SupTech offers opportunities to optimise operational processes, including the efficient collection and management of data, as well as the implementation of more advanced and robust market surveillance systems. By embracing SupTech, supervisors could also move from a purely defensive supervisory approach to a more predictive one.

However, the establishment of a comprehensive EU-wide SupTech strategy poses a number of challenges for EU policymakers and financial authorities alike. Since these challenges have already been extensively discussed in the literature,[891] in the following we only provide for a concise summary, encompassing (*i*) organisational, (*ii*) legal, and (*iii*) reputational key considerations.

i. Building Organisational Capacity

In embracing SupTech, public authorities face the overarching challenge of developing an adequate organisational capacity. This endeavour involves not only conducting research and investing in innovative technologies, but also hiring and retaining highly skilled personnel capable of having a comprehensive understanding on AI, and especially ML, and related subjects, including data science, software engineering, etc.[892]

With the growing adoption of SupTech, moreover, supervisory tasks and processes will inevitably become more automated and data-driven. This does not imply that human judgment will lose its importance. On the contrary, the human element will continue to maintain a decisive role, especially in view of the risks posed by automation and its ethical-legal implications. Accordingly, SupTech must be perceived

[891] *See, e.g.*, Luca Enriques, 'Financial Supervisors and RegTech: Four Roles and Four Challenges' (2017) Revue Trimestrielle de Droit Financier 53 <https://ssrn.com/abstract=3087292> accessed 17 July 2024; Zeranski and Sancak (n 841), discussing a set of fundamental pillars for the effective digital transformation of financial supervision.

[892] *E.g.*, Enriques (n 891); ESMA (n 821) 16-17.

as a means of increasing human capability in the supervision of market conduct rules, rather than as a replacement for the human factor.[893]

It is important to note, moreover, that in order to effectively operationalise a SupTech strategy at the European level, policymakers and financial regulators will need to establish collaborative relationships with all the various stakeholders involved, including market participants and civil society, to ensure that the SupTech strategy is aligned with both market and public interests, including the promotion of efficient, competitive, fair, safe and stable markets. This multi-stakeholder collaboration ultimately aims to create a safe and reliable RegTech/SupTech ecosystem, improving the effectiveness of regulation for the good of society as a whole.[894]

ii. Avoiding New Legal Pitfalls

The establishment of an EU-wide SupTech strategy brings forth new legal risks for public authorities. First, when engaging in contracts with third-party providers, public authorities must ensure the presence of an appropriate legal framework governing their economic and legal relationships with these actors.[895] These agreements are essential to account for and mitigate the potential risks associated with such partnerships, including possible negative repercussions for institutional transparency, accountability, and independence. Indeed, increased reliance on technology companies may introduce new risks of regulatory capture, where undue influence from technology providers may compromise the integrity of public authorities. The occurrence of these risks underscores the need to establish robust institutional

[893] *See, e.g.*, FSB (n 840); Azzutti, Batista, Ringe (n 880), however focusing on the case of EU banking supervision.

[894] *Cf.* Buckley and others (n 838) 32-33.

[895] *E.g.*, Coglianese and Lai (n 397) 17-19.

safeguards in order to maintain regulatory autonomy as well as prevent any conflicts of interest.[896]

Second, in adopting complex and opaque ML methods, public authorities must prioritise the related ethical-legal implications in terms of transparency and accountability. In fact, the inability to understand and explain the functioning of their systems may expose supervisors to new challenges, including supervisory failures, maladministration, and potential liability.[897] Therefore, addressing issues of transparency, interpretability, and explainability in the adoption of ML-based SupTech solutions becomes critical to ensure legality but also trust in supervisory procedures.[898]

Third, the adoption of innovative technologies without being supported by adequate check and balance mechanisms could unjustifiably expand the powers of public authorities beyond their statutory boundaries. This scenario may give rise to a number of legal challenges, especially if the use of technology is hidden from democratic control, raising concerns of opacity and potential abuse of authority.[899] It is therefore imperative that public authorities establish strong governance frameworks, legal safeguards, and accountability mechanisms to mitigate the aforementioned ethical-legal challenges associated with the implementation of a SupTech strategy.

iii. Ensuring Overall Trust

SupTech offers the potential to improve effectiveness and efficiency in the supervision of market conduct, ultimately strengthening society's trust in public authorities and

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[896] *E.g.*, Batista and Ringe (n 839) 220, highlighting the new risks of regulatory capture by market actors leveraging the role of technology.

[897] *See* footnotes n. 877-880 and accompanying text.

[898] *See, e.g.*, Azzutti, Batista and Ringe (n 880).

[899] *See, e.g.*, Coglianese and Lai (n 397); footnote n. 880.

the overall supervisory framework. Yet, there are also some new reputational risks that need to be addressed in order to maintain public trust in a SupTech ecosystem.[900]

Failure to overcome the organisational and legal challenges described above can undoubtedly create much of the reputational risks faced by public authorities adopting SupTech. In addition to these challenges, reputational risks due to cybersecurity issues should also be mentioned. Indeed, in an increasingly technology-dependent regulatory ecosystem, safeguarding cybersecurity is a crucial element to foster trust among all stakeholders, including market players and civil society. Protecting against cyber threats is essential to ensure the reliability, integrity and security of SupTech tools and infrastructures, thereby building trust in regulatory processes and systems.[901]

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Overall, by diligently addressing organisational, legal, and reputational challenges, public authorities can unlock the full potential of SupTech. These steps are key to creating a reliable and secure SupTech ecosystem at the EU level. Through these efforts, public authorities can fulfil their oversight mandate more effectively and efficiently while increasing the trust of all relevant stakeholders. In the context of market conduct supervision, this becomes especially important to ensure market integrity in AI-dominated capital markets.

E. Towards an EU-wide SupTech strategy

Although we do not foresee any insurmountable obstacles for EU financial supervisors in adopting more SupTech solutions within the current market conduct supervision framework, progress towards an EU-wide SupTech strategy requires the establishment of effective cross-border market and market surveillance. To achieve this objective, two

[900] *E.g.*, Coglianese and Lai (n 397) 19-21; and Zeranski and Sancak (n 841).

[901] *See, e.g.*, di Castri, Grasser and Kulenkampff (n 901) 31.

key aspects demand careful consideration from EU policymakers, both from a legal and institutional perspective.

First, the role of data merits thorough examination. AI/ML tools rely on high-quality and readily available data to perform effectively. In the real world, much of the data used by supervisors to feed market surveillance systems is submitted by regulated entities such as investment firms and trading venues. Inaccurate or erroneous data can significantly impair AI-enabled market conduct supervision, potentially leading to biased outcomes or false-positive and false-negative issues in market surveillance. In all these circumstances, so-identified 'unusual' patterns can either indicate actual instances of manipulation or result, for instance, from biased outcomes due to incorrectly reported data. Although misreporting can constitute a violation under MiFID II and hold regulated entities liable, it can also hinder the accuracy of market surveillance outcomes. Thus, any progression towards an EU-wide SupTech strategy would likely require a reconsideration of the existing regulatory data reporting architecture and data governance.[902] This may also entail a paradigm shift from 'push' to 'pull' reporting approaches to ensure data quality.[903] Under the 'pull' reporting approach, supervisors would directly and automatically gather regulatory data upon requests, according to standardised formats and specific modalities.[904] Establishing an integrated and unified digital reporting system, akin to a Big Data architecture for trading data and other pertinent market data, would greatly benefit EU market conduct supervision.[905] As a side effect, however, these developments in the supervisory framework could also generate higher costs for regulated entities, thus affecting the competitiveness and the market structure of the industry.

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902 *See* footnote n. 820 and 821 and accompanying text.

903 *See, e.g.*, Georgosouli and Okonjo (n 820) 236-238.

904 Ibid.

905 *See, e.g.*, Zeranski and Sancak (n 841).

Rethinking and redesigning regulatory data governance frameworks may prompt EU policymakers to contemplate further centralising supervisory tasks at the supranational level to establish an effective EU-wide SupTech structure. This last consideration brings us to the second aspect, which revolves around determining the most suitable authority to spearhead an EU-wide strategy for market conduct supervision. While SupTech can facilitate some level of cross-market and cross-border surveillance through enhanced convergence in supervisory strategies and improved information exchange among NCAs and ESMA, the current rather decentralised approach to market conduct supervision in the EU may not be optimal for ensuring comprehensive market surveillance against AI market manipulation. Therefore, a greater level of centralisation within ESMA may be desirable as a future policy measure to promote truly integrated EU capital markets.[906]

ESMA has increasingly been entrusted with direct supervisory powers in various policy domains in recent years.[907] Building on this trend, considering the growingly EU-wide scope of AI trading, it might be reasonable to assign incremental supervisory powers to ESMA in the field of market surveillance. This policy move could be justified, for instance, under the principle of subsidiarity, as discussed in this chapter. By centralising supervisory tasks at ESMA and empowering it with expanded responsibilities in market surveillance, the EU can foster a more integrated approach to market conduct supervision, also thanks to SupTech implementation.

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906 *Cf.* Martin Arnold, 'Europe Needs Its Own SEC, Says Christine Lagarde: ECB President Says Consolidation among Region's Exchanges Would Plug Substantial Funding Gap' (*Financial Times*, 17 November 2023) <https://www.ft.com/content/acfc67d9-7f2a-4199-9c79-405fef9cb195> accessed 17 July 2024.

907 For a critical account of recent reforms centralising supervisory powers on ESMA, see Fabio Bulfone and Agnieszka Smoleńska, 'The Internal and External Centralisation of Capital Markets Union Regulatory Structures: The Case of Central Counterparties' in Adrienne Héritier and Magnus G Schoeller (eds), *Governing Finance in Europe* (Edward Elgar Publishing 2020) 52-78 <https://doi.org/10.4337/9781839101120.00010> accessed 17 July 2024.

Overall, while challenges exist, EU financial supervisors can navigate the path towards a more comprehensive SupTech strategy within the market conduct supervision framework. Emphasising the importance of data quality, revaluating reporting architectures, and potentially centralising supervisory tasks are key considerations for policymakers in fostering an effective and harmonised EU-wide SupTech approach.

7.4 Enabling Private Enforcement: Is There a Role for Market Manipulation 'Bounty Hunters'?

Possible alternatives for strengthening market conduct supervision could also include the emergence of new solutions from the market itself. Thus, in this section, we explore the potential introduction of a new participant in the already intricate landscape of market conduct actors: i.e. the 'market manipulation bounty hunters'.[908]

Given the challenges facing public authorities in identifying even the most conventional forms of algorithmic manipulation, it becomes necessary to consider new institutional strategies for identifying the most sophisticated forms of algorithmic market manipulation. In this context, the concept of 'bounty hunters' may offer an interesting market-based solution, an approach that has already been explored to address specific issues in economic law and regulation, such as in antitrust domain.[909]

In picturing the possible future role of these new players, it is safe to assume that only licensed 'market manipulation bounty hunters' will be able to take part to the

908 To the best of the author's knowledge, this dissertation is the first scholarly work to discuss 'bounty hunters' within the EU capital markets context. For a first exploration of the same idea from a global perspective, see Miles Kellerman, 'Surveillance Games: The International Political Economy of Combatting Transnational Market Abuse' (DPhil thesis, University of Oxford, 2020) <https://ora.ox.ac.uk/objects/uuid:3f22ea5c-8ce3-4574-9ede-886c88aa0423> accessed 17 July 2024.

909 *See, e.g.*, Aleksandra Lamontanaro, 'Bounty Hunters for Algorithmic Cartels: An Old Solution for a New Problem' (2020) 30 Fordham Intellectual Property, Media and Entertainment Law Journal 1259 <https://ir.lawnet.fordham.edu/iplj/vol30/iss4/6> accessed 17 July 2024.

supervisory game. They would assume responsibility for directly supervising capital markets across multiple jurisdictions. In return for a fee, bounty hunters would then be incentivised to scrutinise market data, identify unusual trading patterns, and report suspicious transactions to competent authorities.[910] Thus, complementing existing whistle-blower programs, the institutionalisation of 'market manipulation bounty hunters' can provide these private organisations with economic incentives to actively monitor EU capital markets. The role of bounty hunters seems particularly valuable the area of combatting 'cross-market' and 'cross-border' forms of market manipulation,[911] thus filling the main gaps in the current supervisory system.

To establish the figure of 'market manipulation bounty hunters', however, EU policymakers should develop a specific legal framework that addresses critical aspects such as licensing and remuneration structures.[912] It is important to note that 'bounty hunters' are not in themselves a panacea. And, in fact, any decision to introduce these actors must carefully balance potential risks and benefits associated with deploying private agents to enforce market conduct rules.

On the one hand, 'market manipulation bounty hunters' can be expected to strengthen enforcement efforts by expanding market surveillance coverage, providing more expertise, allocating dedicated resources, and offering positive incentives for detecting and reporting suspicious transactions.[913] All these aspects can contribute to greater 'certainty of punishment' against cases of market manipulation by AI trading, thereby strengthening the credibility of deterrence.

910 Kellerman (n 174) 242.

911 Ibid 243.

912 Ibid 247.

913 Ibid 248.

On the other hand, the introduction of 'market manipulation bounty hunters' can also give rise to new market and regulatory failures. One primary concern is the possibility of overdeterrence.[914] 'Bounty hunters' may report more instances of suspicious trading conduct than necessary or even engage in false reporting, thereby exacerbating issues related to false positives.[915] Motivated by the pursuit of profits, in fact, these private enforcers might face great incentives to identify even trivial or insignificant cases of suspected manipulation. Moreover, just like public authorities or market actors with delegated regulatory responsibilities (e.g., trading venues), 'bounty hunters' are not immune from the risk of 'capture' by industry players. Lastly, the effectiveness of 'bounty hunters' could also be jeopardised by not entirely cooperative relationships with financial supervisors, which could give rise to unhealthy and counterproductive forms of competition among the two enforcers.[916]

Overall, while the idea of introducing 'market manipulation bounty hunters' into the EU enforcement landscape is undeniably innovative and is worth exploring to offer a potential solution to enhance the effectiveness of market conduct rule enforcement. The concept involves a battle-to-the-last-algorithm scenario between manipulators and bounty hunters, which could align technological innovation with economic objectives closer to the need of the EU society. Moreover, with a robust legal framework in place, 'bounty hunters' can deliver anticipated benefits without significantly introducing new risks to market integrity. In particular, they can help improve the regulatory science of financial regulators, which, by working closely with

914 On the risk of overdeterrence due to the activity of private enforcers like 'bounty hunters', see Amanda M Rose, 'Reforming Securities Litigation Reform: Restructuring the Relationship between Public and Private Enforcement of rule 10B-5' (2008) 108(6) Columbia Law Review 1301, 1326-1330 <ttps://www.jstor.org/stable/40041787> accessed 17 July 2024.

915 Kellerman (n 174) 249.

916 Ibid 250.

market experts, could learn and increase their expertise on the use of technology in capital markets and develop a scientific mindset in combating market manipulation.

7.5 Conclusion

In highlighting the importance of robust enforcement complementing financial regulation, this chapter has stressed the synergetic link between enforcement effectiveness and the quality of financial supervision.[917] However, within the rapidly evolving landscape of algorithm-dominated capital markets, the increasing sophistication of ML-based trading strategies undermines the effectiveness of market conduct supervision.

Our analysis leads to three primary considerations. First, financial regulators and supervisors' limited understanding of AI and data technologies—e.g., about employed ML models, systems' capabilities and limitations, etc.—places them at a profound informational disadvantage compared to entities that develop and use AI tools. Moreover, the proprietary nature of these AI systems further hinders supervisory oversight, thus compromising the ability of authorities to monitor the impact of technological change on market functionality and financial regulation.

Second, the underinvestment in technology leaves regulatory bodies technologically inferior to private entities. As a result, market surveillance systems often prove ineffective in detecting sophisticated manipulative strategies that optimise trading to mask it from legitimate trades.[918]

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[917] In the context of market manipulation, this entails the ability of supervisory authorities to detect, investigate, and prosecute instances of market misconduct in a cost-efficient manner and within a reasonable timeframe, while also guaranteeing private interests in pursuing legal action. *See generally* John Armour and others, 'Supervision and Enforcement of Financial Regulation' in John Armour (ed), *Principles of Financial Regulation* (Oxford University Press 2016) 577-596.

[918] *Cf.* FSB (n 150) 36.

Third, although efforts exist to enhance real-time market surveillance, supervision largely remains a reactive (i.e. *ex-post*) activity. Additionally, market conduct supervision is fragmented across individual and national markets and heavily relies on market participants' technical and organisational capabilities to conduct delegated supervisory responsibilities. While some *ex-ante* supervisory mechanisms exist, they typically necessitate substantial investments by market players. Hence, their effectiveness ultimately rests on private actors' commitment to social responsibility.

Nevertheless, the chapter forwards promising proposals to enhance financial regulation and supervision in the face of these challenges. It examines how financial regulators can leverage ML methods to understand and regulate AI-enabled market manipulation more effectively. By integrating ML with ABM methods, regulators may gain insights into market participants' observable behaviour, including RL-based trading agents, enhancing regulatory and auditing capabilities. The strategic use of SupTech offers an innovative means for regulators to assess algorithms based on 'good market conduct' standards, whose establishment will, however, necessitate adjustments in Level 2 regulation—i.e. technical implementing measures of the European Commission in consultation with EU financial supervisors. This reform process needs to involve multi-stakeholder collaboration, including regulators and industry stakeholders such as investment firms and trading venues, on aspects of standardisation, measures, and benchmarks pertaining to permissive conduct.

Looking forward, advancements in RegTech and SupTech offer the prospect of enhanced auditing frameworks and automated enforcement of rules for AI systems, fostering a future of AI-powered market conduct supervision. In this regard, innovative technical solutions such as machine-readable regulation and XAI tools hold valuable premises.[919] Despite persisting challenges, market supervisors' eventual transition

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[919] *See generally* FSB (n 849) 31-34.

towards greater reliance on AI-powered technology heralds a coming data-centric era: 'algorithmic financial supervision'.[920]

[920] The term is borrowed from Georgosouli and Okonjo (n 904) 218, defining "*algorithmic financial supervision" as "a decision-making system that undertakes regulatory activities by continuously generating knowledge through computation of real-time data collected from the regulated environment, in order to optimise regulatory processes*".

8. AI Governance in Capital Markets: From the Principle of Technology Neutrality to an Engineering-Based Regulatory Approach

In the previous chapters, we have explored how the integration of ML methods into AI trading creates growing challenges to existing regulatory frameworks to ensure the governance of risks arising from the use of sophisticated technology. Specifically, the current regulatory paradigm, built upon the principle of technology neutrality, may no longer be equipped to govern the risks emerging from the latest generation of AI trading powered by ML.[921]

Our analysis has highlighted how specific ML methods can introduce novel threats to market integrity, including novel variants of market manipulation and even algorithmic collusion, often independent of human intention. These scenarios underscore the constraints of applying established market abuse regulatory frameworks, thus leaving markets vulnerable to manipulation by increasingly 'intelligent' algorithms. Although regulations for algorithmic trading aim to mitigate technology-related risks, the ongoing and fast-paced advancements in AI accentuate the limitation of legal systems in shaping algorithmic behaviour towards socially acceptable and positive outcomes. Within this context, 'Deep Computational Finance' techniques, particularly RL-based agents, pose significant and complicated governance challenges compared to traditional AI approaches in algorithmic trading (e.g., GOFAI).

The current governance strategy for algorithmic trading is a blend of sector-specific legislations (i.e. MiFID II), setting forth foundational yet high-level organisational requirements, as well as self-regulation by market participants, tasked with internally formulating and implementing governance procedures and systems to

[921] *Cf, e.g.*, Rodríguez de las Heras Ballell (n 664) 303 and 314.

best adhere to regulatory requirements. The prevailing regulatory approach to the governance of algorithmic trading is primarily principle-based rather than rule-based, granting investment firms the autonomy to strategise their regulatory compliance approach. However, despite their different risks, this approach does not adequately consider the distinction between various AI methods. This situation becomes particularly concerning considering the mounting risks posed by specific ML methods. Hence, the challenges of AI alignment may be significant under the current governance approach.

Therefore, given the widening gap between law and technology, there is a need to find optimal ways to ensure the safe and responsible adoption of AI, particularly ML methods, in financial trading. One pivotal challenge is to strike a balance between allowing technology to pursue the business interest of private organisations and aligning it with the broader public interests of regulatory goals, such as market integrity. As a central policy task, this challenge requires determining the most effective approach to AI governance in financial trading. To accomplish this goal, the remainder of this chapter is organised as follows. Firstly, we will scrutinise the deficiencies of current regulatory frameworks that, due to ML, may fail to govern risks associated with AI trading (Chapter 8.1). Subsequently, we will review some of the emerging legal theories that might assist us in addressing the governance challenges related to AI trading (Chapter 8.2). Following this, we will look at the most significant policy trends in AI governance in the financial sector and their potential to address the new risks to market integrity introduced by ML methods (Chapter 8.3). Recognising the shortcomings of current algorithmic trading governance frameworks to address the specificities of ML and its additional risks, we will propose an innovative approach to regulate AI trading. Partly inspired by the EU AI Act, our approach goes beyond the technology-neutral principle to embrace an engineering-based approach to regulation from the perspective of the 'AI lifecycle' (Chapter 8.4). Finally, we will summarise the chapter and provide some concluding remarks (Chapter 8.6).

8.1 Challenges to Effective AI Regulation in Financial Trading

Current regulatory frameworks are designed to enhance investor protection, maintain fair, efficient, and transparent markets, as well as safeguard financial stability. As seen in Chapter 5, the governance of algorithmic trading is addressed by *lex specialis*, which aims to ensure both technical and operational safety. Relatedly, regulatory requirements cover aspects of model transparency, risk management, regulatory compliance, and human accountability, among others.[922] However, when closely reviewing the existing regulatory regimes for algorithmic trading, there are some reasons to believe that they may not take into account the additional risks introduced by advances in AI, particularly ML methods.

One key requirement for financial institutions is to ensure the predictability, controllability, and explainability of the outcomes of their algorithmic trading systems, regardless of the specific AI approaches employed. Thus, even when adopting ML methods, investment firms and their human staff must be in a position, at least *de jure*, to comprehend and reason about the market activity of their trading systems in order to comply with the law. As part of responsible professional conduct, human experts in charge of ML trading system operations must be accountable to various stakeholders (e.g., their boss, clients, and financial supervisors) for the negligent or improper use of technology. Despite these requirements, however, current regulatory frameworks do not seem able to provide clear and consistent guidance on how to ensure effective control and adequate transparency about the use of increasingly sophisticated ML methods.[923]

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[922] This dissertation focuses specifically on the legal and regulatory regimes in the EU, which can be considered as the most comprehensive framework on the governance of algorithmic trading. For a comparative analysis including the most advanced legal systems worldwide, see Kee H Chung and Albert J Lee, 'High-frequency Trading: Review of the Literature and Regulatory Initiatives around the World' (2016) 45(1) Asia-Pacific Journal of Financial Studies 7 <https://ssrn.com/abstract=2697604> accessed 17 July 2024.

[923] *But see* footnotes n. 92 and 603.

Although existing regimes may partially address some of the risks to the fair and orderly functioning of markets associated with AI trading, yet they appear to be based on somewhat outdated assumptions that may not fully accommodate the growing sophistication of contemporary and future algorithmic trading. Due to their increasing levels of autonomy, complexity, and opacity, certain ML-based applications present significant challenges in understanding, trusting, and communicating AI-generated outcomes and their impact on market behaviour. As a result, market integrity and stability might be put at risk, highlighting a pressing need for innovative regulatory approaches able to effectively account for the specificities of ML-based trading and mitigate the potential risks associated with it. Below we present a summary of the shortcomings of current regulatory and governance frameworks, based on our investigations in previous chapters.

A. Legal definition of algorithmic trading

One initial concern relates to the exact scope of application of the regulation of algorithmic trading with respect to various AI approaches. Indeed, there is no universally accepted legal definition of algorithmic trading across jurisdictions. Yet most legal systems tend to subject HFT—regardless of the specific use of AI, particularly ML methods—to stricter regulatory requirements due to the perceived higher potential to distort markets and even cause systemic risk.[924]

With regard to the EU legal framework, in the literature it is argued that the definition of algorithmic trading can be considered both over- and under-inclusive.[925] On the one hand, it is too broad because it also encompasses those automated trading applications where the human factor is still relevant for final decision-making. On the other, it is too narrow as it excludes some unsophisticated forms of execution-only

[924] *See, e.g.*, Karremans and Schoeller (n 78).

[925] *See, e.g.*, Martins Pereira (n 84) 298-300.

trading algorithms, which however history shows their potential to disrupt and harm markets.[926]

Apart from that, current legal frameworks—including in the EU—do not address the specific application of various ML methods and AI-based techniques in any relevant way. Since it relies on the principle of technology neutrality, MiFID II does not distinguish between different uses of trading technology, despite the fact that the level of associated risks can vary widely depending on the complexity and capabilities of specific AI applications, especially due to ML. As we shall see, this lack of regulatory differentiation between different uses of technology, particularly ML methods, can create challenges for investment firms in ensuring effective accountability and governance on the one hand, and complicate the work of financial regulators in conducting appropriate oversight of algorithmic trading systems on the other. As different AI trading applications can carry very different levels of risk, different regulatory treatments should therefore be applied to ensure the ability to monitor their proper and responsible operation, including compliance with market conduct rules.

Overall, there is ambiguity, partly due to the predominant principle of technology neutrality, about the scope and effectiveness of the current rules applicable to various algorithmic trading practices. Since they apply indiscriminately to both less sophisticated and more sophisticated forms of algorithmic trading, AI governance in financial trading may not be entirely guaranteed, especially with respect to specific uses of ML.

B. Regulatory requirements targeting algorithmic trading

Chapter 5 highlights that, under MiFID II, regulatory requirements on the governance of algorithmic trading encompass both *ex-ante* and *ex-post* regulatory measures targeting both investment firms using algorithmic trading, regulated venues that host

[926] Ibid.

algorithmic trading, and DEA providers—those firms providing for direct market access to other algorithmic traders. Below, we illustrate how the regulatory requirements may fail to provide an adequate governance framework for AI trading that is powered by ML methods.

i. Requirements on investment firms

The tasks of mitigating risks inherent to algorithmic trading are mostly left to their developers and users.[927] The EU legal framework places specific legal and organisational requirements on investment firms to ensure the effective governance of algorithmic trading. However, due to technical specificities of ML-based applications, these requirements may be doomed to fail in their attempt to promote trustworthy adoptions.

To begin with, investment firms must notify trading venues and competent authorities about their use of algorithmic trading, provide certain details about their trading systems (e.g., trading strategies employed, risk controls in place, parameters relevant to execution, etc.), with additional regulatory burden for those firms conducting HFT or market making activities.[928] Additionally, to enable market conduct supervision, the activity of algorithmic traders needs to be flagged, and investment firms must keep records of their trading history to support regulatory compliance and oversight activities.[929]

Moreover, the law prescribes a number of organisational requirements to help companies monitor and control the market conduct of algorithmic trading, emphasising the critical importance of the enterprise risk management and compliance function. For instance, 'strong' *de jure* requirements are imposed on the testing,

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927 *See* discussion in Chapter 5.3.

928 *See* footnotes n. 591 and 592 and accompanying text.

929 *See* footnote n. 630 and accompanying text.

validation, and deployment phases of algorithmic trading to ensure reliable and legally complaint applications.[930] Furthermore, in order to limit risks to the orderly functioning of markets, investment firms are required to take precautionary measures to avoid unintended, biased or unlawful outcomes. These requirements typically involve substantial investment in internal systems and controls to monitor the proper functioning of algorithmic trading—i.e. that it behaves as intended—and the implementation of technical and organisational measures to identify and mitigate the risks of market disruption and manipulation.[931]

Yet implementing the abovementioned regulatory requirements can be challenging in the context of ML-based trading. Investment firms are required to adopt adequate control measures and systems, which however entail costly investments in technological solutions and require high-level human expertise to make them operational.[932] As a result, private organisations may not always face the right incentives to take all the necessarily precautionary steps to meet regulatory expectations.[933]

The integration of ML into algorithmic trading systems casts doubts about investment firms' ability to meet compliance with regulatory requirements. In particular, compliance divisions are required to possess at least "a general understanding" of how algorithmic trading systems operates.[934] Regulatory

930 *See* footnotes n. 593-603 and accompanying text.

931 *See* footnotes n. 609-614 and accompanying text.

932 *See, e.g.*, Zetzsche and others (n 624).

933 *Cf.* FINRA, 'Regulatory Notice 15-09 on Effective Supervision and Control Practices for Firms Engaging in Algorithmic Trading Strategies' (26 March 2015) <https://www.finra.org/rules-guidance/notices/15-09> accessed 17 July 2024, stating that "*in addition to specific requirements imposed on trading activity, firms have a fundamental obligation generally to supervise their trading activity to ensure that the activity does not violate any applicable FINRA rule, provision of the federal securities laws or any rule thereunder*."

934 *See* RTS 6 art 2(1).

compliance, for instance, presupposes that the risk and compliance staff have a basic understanding of ML and associated risks, so as to empower them with sufficient knowledge to challenge human developers and users of AI trading systems whenever required.[935] These requirements must apply regardless of the use of specific AI approaches. Thus, the use of complex and opaque ML methods cannot allow investment firms to circumvent this fundamental organisational requirement.[936]

Moreover, to effectively control the market behaviour of trading algorithms, investment firms should always be in a position to ensure that algorithmic trading "does not behave in an unintended manner".[937] This is accomplished through behavioural testing before implementation and ongoing monitoring of trading by automated surveillance systems. But again, ML poses some challenges to the effectiveness of these control measures. On the one hand, it may be hard or even just not feasible to know *a priori* how an ML-based trading system will operate once live. Stress-testing a trading algorithm prior to its actual implementation, in fact, may not suffice to ensure that it will not behave in a disorderly or unintended manner.[938] Thus, the effectiveness of testing conducted by firms themselves is thus in question. This is mainly because effective regulatory compliance largely depends on extensive testing and the availability of realistic scenarios, including the ability to understand the effects on and reactions of markets and other traders.[939] On the other hand, while *ex-post* surveillance of market behaviour can generally contribute to identifying and mitigating some of the risks associated with automated trading, it does not suspend the responsibility of investment firms to understand and control their trading

935 *See* RTS 6 art 3(4).

936 *See, e.g.*, AFM (n 105) 24.

937 *See* RTS 6 art 5(4).

938 *See* footnote n. 936.

939 *E.g.*, ibid.

algorithms.[940] In sum, effective governance not only requires regulation and oversight focused on the observable outcomes in markets of trading systems, but also, and more importantly, on the processes underlying the entire AI lifecycle, on which the operations of AI systems ultimately depend.

ii. Requirements on trading venues

To protect markets against the occurrence of negative externalities, regulated markets that host algorithmic trading have some delegated regulatory responsibility to fulfil under MiFID II.[941] However, when confronted with ML-powered trading, some doubts remain about the effectiveness of these requirements in ensuring effective governance, in particular the mitigation of risks arising from unintended consequences and/or market misconduct.

First, consider the role of trading venues in acting as the first checker of the (mis-)behaviour of trading algorithms. As previously discussed, market operators play a significant part in the auditing and control of algorithmic market behaviour on their platforms.[942] In auditing, for instance, they are usually involved in the testing of trading algorithms by providing testing facilities such as simulation environments.[943] When an algorithmic trader operates in a given regulated market, one may therefore assume that this is done in accordance with market conduct rules, as typically ascertained by the fulfilment of behavioural testing obligations. It is worth recalling that, prior to actual implementation on real markets—but also at any substantial modification of a given trading system or strategy—investment firms must undergo both behavioural and conformance testing to ensure their regulatory compliance, including with market

[940] *E.g.*, ibid.

[941] *See* Chapter 5.3.B.

[942] *See* footnotes n. 631-637 and accompanying text.

[943] *See, e.g.*, Raschner (n 86).

conduct rules. As with investment firms, trading venues face similar challenges in ensuring the effectiveness of existing testing frameworks when it comes to ML-based trading strategies. While these frameworks may provide some level of assurance, they have limitations in scope and, as such, they may not fully guarantee that trading systems will not behave disorderly or in unintended ways.[944] Especially when ML is involved, additional measures to traditional testing frameworks may need to be considered to ensure proper governance of algorithmic trading.

Second, trading venues can limit the boundaries of the action space of trading algorithms through direct market interventions (i.e. arrangements for electronic trading system operational resilience, circuit-breakers, etc.), which function as guardrails to prevent market disruptions as a last resort, and surveillance of trading activity.[945] With regard to the latter, operators of regulated markets must conduct screening of trading activity in order to detect possible instances of unusual trading. Thus, if a suspicious activity is detected, enforcement collaboration with supervisory authorities can be initiated.[946] In market surveillance, it is noteworthy that trading venues not only apply market conduct rules, as defined by MAR and supplementing regulation but also their specific trading rules. The latter, however, are not necessarily harmonised among competing trading venues.

Yet, as previously observed, market operators as watchdogs are well known to face an incentive dilemma. Indeed, they have to find a compromise between the rigorous screening of trading behaviour—i.e. through both auditing and market surveillance activities—and the objectives of a profit-seeking private business under fierce competitive pressure from alternative venues.[947] On a related note, as investment

944 *See, e.g.*, footnotes n. 631-633.

945 *See, e.g.*, Lee and Schu (n 85) 217-221.

946 *See* footnotes n. 618-622 and 636 and accompanying text.

947 *See* footnote n. 80 and accompanying text.

firms active in algorithmic trading can simultaneously be the operator of a trading platform (e.g., a dark pool), this can lead to possible conflict of interests, which can further constitute a source for ineffective market surveillance.[948]

More generally, being exclusively in charge of the oversight of their own marketplace platforms, trading venues are not in a position to provide cross-market and cross-border market surveillance, which indeed is one of the main limitations of the current supervisory architecture,[949] especially given the market ubiquity that specific ML-based strategies can reach.

iii. Requirements on DEA providers

Ineffective governance of algorithmic trading can occur when algorithmic traders utilise direct market access facilities offered by other investment firms, such as in the context of DEA arrangements. Investment firms lacking direct market access, in fact, can utilise the ICT facilities of host financial institutions (e.g., trading codes) to gain market access and engage in algorithmic trading.

Under MiFID II, providers of market access are responsible for ensuring that guest algorithmic traders comply with regulatory requirements.[950] However, a lack of willingness and ability of DEA providers to audit algorithmic trading for regulatory compliance can result in less rigorous screening of algorithmic systems and their market behaviour. [951] This seems particularly the case whenever DEA clients make use

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948 *See, e.g.*, Busch (n 85) 75; *see also* Stanislav Dolgopolov, 'Legal Liability for Fraud in the Evolving Architecture of Securities Markets' in Walter Mattli (ed), *Global Algorithmic Capital Markets: High Frequency Trading, Dark Pools, and Regulatory Challenges* (Oxford University Press 2018) 272-273 <https://doi.org/10.1093/oso/9780198829461.003.0010> accessed 17 July 2024, providing evidence of the conflict of interest issue from a US perspective.

949 *See* discussion in Chapter 7.2.A; *see also* IOSCO, 'Technological Challenges to Effective Market Surveillance: Issues and Regulatory Tools – Final Report' (April 2013) <https://www.iosco.org/library/pubdocs/pdf/IOSCOPD412.pdf> accessed 17 July 2024.

950 *See* footnotes n. 598 and 618 and accompanying text.

951 *See* Alexander C Culley, 'Does the Deployment of Algorithms Combined with Direct Electronic Access Increase Conduct Risk? Evidence from the LME' (2022) 31(2) Journal of Financial Regulation

of sophisticated ML-based trading systems. Hence, the challenges discussed earlier for trading venues also apply, by analogy, in the DEA context.

C. Opacity and challenges for regulatory compliance

As previously examined, existing regulatory frameworks follow a behaviouristic approach, thus remaining entirely *neutral* with regard to the exact AI-powered technology, particularly ML methods, involved in a given algorithmic trading system. Regulatory focus, thus, is mostly placed on algorithmic trading market behaviour and measurable outcomes (i.e., trading patterns), rather than the sophistication and complexity of AI systems.[952]

Because of an exclusive focus on outcomes, it seems doubtful that current regulatory approaches to the governance of algorithmic trading are well equipped to handle the technical specificities of ML-based systems, particularly the associated risks to the fair and orderly functioning of markets. Indeed, when sophisticated ML methods are involved (e.g., DL), tensions may easily arise in achieving appropriate levels of transparency and ensuring human control and accountability. Issues of transparency in ML becomes of paramount importance in the context of regulatory compliance, as discussed below.

i. Regulatory compliance challenges

At least *de jure*, a 'strong' form of explainability for algorithmic trading systems is required.[953] However, meeting this 'strong' explainability requirement may create friction between achieving the highest level of operational accuracy and reliability and

and Compliance 220 <https://doi.org/10.1108/JFRC-04-2022-0046> accessed 17 July 2024; *see also* ESMA (n 61) 13-15 and 29-32.

[952] *See* footnotes n. 577-579 and accompanying text.

[953] *See* Bibal and others (n 592) 164, arguing that "*[a] total understanding of the model is required [...] in the case of financial algorithms*."

being able to explain the logic behind a given algorithmic market behaviour.[954] In other words, the adoption of ML can frustrate investment firms' ability to meet regulatory expectations in the first place. However, it should be observed that, *de facto*, current legal systems and supervisory arrangements only partially address 'strong' AI explainability, as most compliance exercises rely on self-assessment reports by investment firms and trading venues. The shortcomings of the current regime have been indeed also partly highlighted by ESMA in its 2021 report on the governance of algorithmic trading.[955] Actually, financial regulators can only rely on the annual self-assessment reports submitted by supervised entities in order to determine the latter's compliance with regulatory requirements. As a consequence, competent authorities have no detailed knowledge regarding how firms structure their algorithmic workflow from high-to-low levels of decision-making.

Admittedly, it may be doubtful whether a mere statement of compliance by the same investment firms can really accommodate the increasingly autonomous, sophisticated, and often black box nature of specific ML applications to financial trading (e.g., based on DRL). Not surprisingly, in fact, the same ESMA is considering the merits of introducing a real due diligence process for algorithmic trading systems.[956] A more intrusive supervisory approach could thus be instrumental to limit growing information asymmetries between regulators and regulated entities. Nevertheless, embracing such an approach requires competent authorities to equip themselves with the appropriate knowledge and skills needed to inspect the use of AI systems from a standpoint of their compliance with regulatory requirements.

In view of these considerations, it could be argued that in pursuing the principle of technology neutrality, financial regulation may in part undermine market integrity

954 Ibid.

955 *Cf*. ESMA (n 61) 47-50.

956 *Cf*. ESMA (n 61) 40.

as an unintended consequence. To avoid this risk, financial regulators are therefore required to closely monitor market-driven AI innovation, assess the need to upgrade regulatory frameworks and supervisory tools, and at the same time ensure the promotion of beneficial technology within the industry. As will be discussed later in this chapter, it is desirable that competent authorities play a more active role in regulating technology-related aspects as well as in their oversight (e.g., taking part to due diligence processes). On the other hand, in assessing investment firms' compliance, the auditing of AI trading systems should become an integral part of a periodical review and evaluation process carried out by competent authorities or an independent body.[957] In the area of regulatory compliance, advances in RegTech could help foster a new technology-driven governance paradigm, enabling financial institutions to better understand and explain the behaviour of their AI systems thus better meeting regulatory requirements in terms of transparency and market conduct.[958] Lastly, it is appropriate to reiterate that advancements in SupTech, particularly thanks to ML methods, hold promise for facilitating the oversight of AI trading systems as part of a new generation of supervisory strategies and tools.[959]

8.2 Emerging Regulatory Theories on AI

In light of the methodical-technical peculiarities of ML approaches applied to algorithmic trading and the potential risks to markets introduced by them, one pressing question arises: *Are current regulatory approach able to ensure the effective governance of AI trading?* The answer remains uncertain, prompting a vital discussion among policymakers, legal scholars, as well as experts from other scientific disciplines.

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957 *See, e.g.*, Christian M Stiefmueller, 'The Soul of a New Machine – Promises and Pitfalls of Artificial Intelligence in Finance' (2022) 62 The Human Side of Service Engineering 353, 363-364 <http://doi.org/10.54941/ahfe1002577> accessed 17 July 2024.

958 *See, e.g.*, David McNulty, Andrea Miglionico, and Alistar Milne, 'Technology and the 'New Governance' Techniques of Financial Regulation' (2023) 9(2) Journal of Financial Regulation 255 <https://doi.org/10.1093/jfr/fjad008> accessed 17 July 2024.

959 *See* Chapter 7.3.

In the following, we explore a range of emerging legal theories and policy solutions proposed as fit to cope with the additional risks and associated ethical-legal dilemmas posed by ML applications.

Within the current debate over the regulation of AI, a spectrum of emerging ideas can be observed, from more precautionary approaches to more lenient ones. Some radical views advocate a strong precautionary approach to regulating AI, proposing pre-emptive restrictions or even strict bans on AI systems and applications deemed too risky for society.[960] Now, the main obstacles to these types of proposal may be twofold. On the one hand, they are based on the difficult assumption that a clear distinction can always be drawn between applications of AI that are too risky, hence illegal, and less risky, hence permitted. On the other hand, these approaches clash with some of the basic principles of financial market regulation—i.e. economic freedom, competitiveness, and technological neutrality. Blindly ignoring these principles, however, may hinder technological innovation as defined by the industry, possibly squandering countless opportunities for efficiency gains. In short, these approaches are not in line with the underlying rationale of financial regulation and may ultimately prove counterproductive.

At the other end of the spectrum, instead, are views recommending that policymakers to adopt a 'wait-and-see' approach until the regulatory object becomes clearer, that is, after the concrete risks associated with specific AI applications have actually materialised. This strategy works on the assumption that existing legal concepts, including those underpinning liability rules, and other regulatory instruments of governance (e.g., sectorial legislation or regulatory standards such as guidelines, ethical codes of conduct, or industry best practices) can mitigate many of

960 *Cf*. Adam Thierer, Andrea Castillo O'Sullivan, and Raymond Russell, 'Artificial Intelligence and Public Policy' (2017) Mercatus Research, Mercatus Center at George Mason University, Arlington, VA, 3 <https://www.mercatus.org/system/files/thierer-artificial-intelligence-policy-mr-mercatus-v1.pdf> accessed 17 July 2024; *see also* Commission's White Paper at 10, which mentions the German Data Ethics Commission's five-level risk-based regulatory system proposal, contemplating a total ban on the most dangerous AI applications.

the risks associated with AI.[961] However, also pursuing a 'wait-and-see' approach might be problematic as it may lead to disregarding the potential implications of AI/ML in critical and risky domains for society such as capital markets. As a policy strategy, it seems unwise to wait for accidents or even catastrophic events to occur before taking any policy action.[962] The mere fact that a major risk has yet to materialise should not preclude (free) policymakers and financial regulators from gaining knowledge on AI and its potential to cause harm.[963] AI trading systems may indeed fall into the category of technologies involving inevitable danger or, as Charles Perrow puts it, "normal accidents". Although the risks associated with certain high-risk technology applications may be highly unlikely, their manifestation can have catastrophic consequences for the entire system.[964] Thus, the systemic nature of these risks would urge financial regulators to take a more proactive approach to regulating AI trading.

Overall, continued advances in ML methods and their increasing adoption by market participants require policymakers and regulators to monitor technological developments in order to identify and address potential sources of risk to markets and society as a whole (i.e. including issues related to theoretical limits, validity of open source, data bias, opacity, and cyber threats, etc.). Ignoring these risks could indeed have severe repercussions for market integrity and financial stability, thus jeopardising investor confidence on the fair, safe, and orderly functioning of markets. With such

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961 *See, e.g.*, Reed, Kennedy, and Nogueira Silva (n 707) 10.

962 *Cf.* Iman Anabtawi and Steven L Schwarcz, 'Regulating Ex Post: How Law Can Address the Inevitability of Financial Failure' (2013) 92(1) Texas Law Review 75, 128-131 <https://scholarship.law.duke.edu/faculty_scholarship/3067> accessed 17 July 2024; Jon Truby, Rafael Brown, and Andrew Dahdal, 'Banking on AI: Mandating a Proactive Approach to AI Regulation in the Financial Sector' (2000) 14(2) Law and Financial Markets Review 110 <https://doi.org/10.1080/17521440.2020.1760454> accessed 17 July 2024.

963 Ibid.

964 *See* Charles Perrow, *Normal Accidents: Living with High-Risk Technologies* (Princeton University Press 1999) 16-18; *see also* Anabtawi and Schwarcz (n 962) 93-96, discussing Charles Perrow's theory in the context of how financial regulation should address risks associated with technological innovation.

high stakes, the consequences of inaction could indeed be dire. Hence, in the remainder of this section, we explore some of the possible legal solutions most often discussed in academic and policy circles.

A. Liability rules for AI

One often-debated law area to tackle issues of misconduct and harm by autonomous AI systems concerns liability rules. Several legal scholars, in fact, call for reflection on the necessary revision of liability rules in order to promote legal clarity in accountability and ensure effective compensation for victims, thereby promoting general trust in the functioning of markets.

As previously discussed, an innovative yet seemingly contentious proposal involves conferring legal personhood to autonomous AI agents, thereby holding them directly accountable and liable for their wrongdoing.[965] The idea to grant AI legal personhood is often juxtaposed with the proposal to establish a tailored insurance coverage system.[966] On the bright side, this approach could conceivably imbue markets with the capacity to internalise the costs of regulating AI. On the flip side, it may engender moral hazard and even subject markets to novel sources of systemic risks, not to mention the challenges for insurers in pricing nascent and evolving financial risks associated with AI.

Differently, other views advocate the imposition of a 'strict liability' rule under tort law on those who use and benefit from the operation of AI systems.[967] To some extent, this is also the approach proposed earlier for the case of administrative

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[965] *See* footnotes n. 758-761 and 768-774 and accompanying text.

[966] *See* footnotes n. 802-804 and accompanying text.

[967] *See* footnote n. 801; *see also* Chagal-Feferkorn (n 699) 107-113, arguing that traditional products liability rules could be applied to in the context of certain AI applications; Bathaee (n 76) 931-932, discussing the trade-off between safety and innovation that may arise from the imposition of strict liability rules.

violations of market manipulation, as part of a new multi-level liability regime for market misconduct and harm by AI trading.[968] Nonetheless, the imposition of a blanket strict liability rule in all circumstances of AI misconduct and harm necessitates judicious calibration: liability risk may have a significant chilling effect on innovation, some of which could prove beneficial to society. Consequently, we also highlighted the intricate balancing act that, in the context of our analysis, financial regulators must navigate to safeguard market liquidity, thus efficiency, without sacrificing market integrity. For instance, to provide greater clarity and assurance to market players, financial regulators could furnish more explicit guidelines on permissible market conduct that poses no threat to market quality and integrity, thus does not lead to liability.[969] This would foster a more certain and predictable regulatory environment, allowing market actors to operate with greater confidence within the bounds of the law. Moreover, we also discussed how, in the context of SupTech, the same use of ML methods as analytical tools can help financial regulators better understand the mechanics and cause-effect characteristics of sophisticated forms of market manipulation (e.g., spoofing). This knowledge can contribute to improved regulatory science and be used to achieve greater legal certainty, enabling the establishment of more precise and thus less ambiguous legal prohibitions.[970] But we also outlined a number of organisational, legal and reputational challenges that must be addressed to ensure trustworthy adoption of ML-based SupTech tools.[971]

Overall, the challenges posed by automation in financial trading have sparked a lively debate on how regulation can mitigate risk-taking and moral hazard while fostering innovation. Although liability rules may struggle to be securely applied in the context of ML-based trading systems, they can be complemented by sound regulation

[968] *See* Chapter 6.5.B.ii.

[969] *See* Chapter 6.5.A.

[970] *See* Chapter 7.3.A and 7.3.C.

[971] *See* Chapter 7.3.D.

that addresses governance challenges. Indeed, a number of intriguing ideas for managing the unique risks posed by AI have emerged in recent years alone. Below we focus on some key proposals intended to guide the trustworthy adoption of AI in the financial sector. These proposals prioritise, for instance, techno-legal aspects such as human control and accountability, transparency, as well as other control frameworks such as algorithmic auditing and testing.

B. The 'human-in(-and-on)-the-loop'

Maintaining a 'human-in(-and-on)-the-loop'[972] in AI decision-making processes is an oft-discussed regulatory strategy to promote trustworthy AI adoption in high-risk domains. Given the risks to society that rigged and unstable capital markets can pose, this approach can also find wide application in the financial trading industry. The 'human-in(-and-on)-the-loop' approach, which to some extent is already part of existing governance frameworks as prescribed by MiFID II and MAR, involves assigning specific roles to individuals at different stages of the AI production line, or AI lifecycle, in order to ensure outcome quality, regulatory compliance, human accountability and responsibility.[973] By enhancing transparency and traceability about the actions of the various agents involved in a given AI project, this approach can, for instance, also alleviate difficulties in ascertaining and assigning individual liability.[974]

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972 The term 'human-in(-and-on)-the-loop' is a contraction of the terms 'human-in-the-loop' and 'human-on-the-loop'. While the former concept refers to a type of human-machine interaction in which human experts are actively involved in various stages of AI decision-making, the latter refers to a more distant level of human oversight that requires human intervention only when necessary, thus leaving an AI system able to operate autonomously. For a survey on the concept of 'human-in-the-loop' in ML research, see Xingjiao Wu and others, 'A Survey of Human-in-the-Loop for Machine Learning' (2022) 135 Future Generation Computer Systems 364 <https://doi.org/10.1016/j.future.2022.05.014> accessed 17 July 2024.

973 *See, e.g.*, Jermy Prenio and Jeffery Yong, 'Humans Keeping AI in Check – Emerging Expectations in the Financial Sector' (2021) BIS, FSI Insights on policy implementation No 35, 7, 16 and 17 <https://www.bis.org/fsi/publ/insights35.htm> accessed 17 July 2024.

974 *E.g.*, Zetzsche and others (n 624) 38-39 and 46-48, discussing however all the practical challenges inherent to effectively implementing such an approach.

On the positive side, the 'human-in(-and-on)-the-loop' approach has the potential to strengthen current legal frameworks and mitigate the need for radical law revisions. Recent policy initiatives worldwide have recognised the importance of integrating human intelligence in the AI decision-making process. Some authorities have promoted, through soft law instruments, the adoption of this governance measure by both public and private organisations,[975] especially in risky application domains.[976] The EU AI Act, as prospective first global hard law instrument, is intended to impose to some extent human oversight as a basic requirement for 'high-risk' AI applications.[977]

On the negative side, however some viewpoints suggest that this approach may have some limitations and even introduce new risks to effective governance, particularly the potential for human error and bias in AI decision-making (e.g., due to automation bias). Additionally, mandating 'human-in(-and-on)-the-loop' can entail

975 *See, e.g.*, European Commission, High-Level Expert Group on Artificial Intelligence, *Ethics Guidelines for Trustworthy AI* (European Commission 8 April 2019) 14-20 <https://www.europarl.europa.eu/cmsdata/196377/AI%20HLEG_Ethics%20Guidelines%20for%20 Trustworthy%20AI.pdf> accessed 17 July 2024, discussing seven key requirements for the trustworthy implementation of AI, including: (i) human agency and oversight; (ii) technical robustness and safety; (iii) privacy and data governance; (iv) transparency; (v) diversity, non-discrimination and fairness; (vi) societal and environmental wellbeing; (vii) accountability. For a comprehensive examination of the concept of the 'human-in-the-loop' in law, see Rebecca Crootof, Margot E Kaminski, and W Nicholson Price II, 'Humans in the Loop' (2023) 76(2) Vanderbilt Law Review 429 <https://wp0.vanderbilt.edu/lawreview/wp-content/uploads/sites/278/2023/03/Humans-in-the-Loop.pdf> accessed 17 July 2024.

976 *See, e.g.*, Commission's White Paper at 18-22, discussing six key requirements for 'high-risk' AI applications, including: (i) training data; (ii) data and record-keeping; (iii) information to be provided; (iv) robustness and accuracy; (v) human oversight; (vi) specific requirements for certain AI applications). For a discussion on the role of 'human-in-the-loop' regulation to promote trust in AI, see Stuart E Middleton and others, 'Trust, Regulation, and Human-in-the-Loop AI within the European Region' (2022) 65(4) Communications of the ACM 64 <https://dl.acm.org/doi/pdf/10.1145/3511597> accessed 17 July 2024.

977 *See* AI Act art 14. For a critical discussion on the matter, see Michael Veale and Frederik Zuiderveen Borgesius, 'Demistifying the Draft EU Artificial Intelligence Act' (2021) 22(4) Computer Law Review International 97, 103-104 <https://doi.org/10.9785/cri-2021-220402> accessed 17 July 2024.

rising costs and greater operational complexity for those organisations called to implement it.[978]

Despite these concerns, it still safe to assume that incorporating the human element into AI decision-making is a crucial factor in building trust and ensuring ethical and responsible practices even in the world of financial trading. Nevertheless, while the existing regulatory framework mandate human involvement at different stages of algorithmic decision-making—such as, for instance, the oversight by human traders, risk management and compliance personnel—at the same time, it lacks specificity. In other worlds, regulatory requirements for the governance of algorithmic trading mainly entail high-level principles rather than specific rules. Moreover, based on the 'technology neutrality' principle, these requirements apply uniformly to all regulated trading systems, irrespective of the particular ML methods employed.[979]

C. AI Transparency

Adequate levels of transparency[980] in algorithmic trading are essential for human users to meaningfully control its functioning and market behaviour. Without proper understanding and explanations of algorithmic outcomes, ensuring compliance with regulatory requirements (e.g., market abuse regulations) as well as human

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978 *Cf.* Therese Enarsson, Lena Enqvist, and Markus Naarttijärvi, 'Approaching the Human in the Loop – Legal Perspectives on Hybrid Human/Algorithmic Decision-Making in Three Contexts' (2022) 31(1) Information & Communications Technology Law 123, 149-152 <https://doi.org/10.1080/13600834.2021.1958860> accessed 17 July 2024, discussing the legal and ethical implications of human oversight of AI systems; Wu and others (n 972) 376-377, addressing some of the challenges faced by human experts in the oversight of AI systems.

979 The 'technology neutrality' approach is one of the main recurring elements of current financial regulatory regimes. It allows regulators to avoid overly prescriptive requirements, leaving regulated entities to seek the most appropriate solutions to ensure their regulatory compliance. *See* Wojtek Buczynski and others, 'Hard Law and Soft Law Regulations of Artificial Intelligence in Investment Management' in Emilija Leinarte and Oke Ududu (eds), *Cambridge Yearbook of European Legal Studies* (Cambridge University Press 2022) 282 <https://doi.org/10.1017/cel.2022.10> accessed 17 July 2024.

980 For an in-depth look at the interaction between different dimensions of transparency and trust in ML-based systems, see Zerilli, Bhatt and Weller (n 272).

accountability and liability for wrongdoing become a daunting task. This issue is particularly relevant in the case of certain ML-based trading methods due to their autonomous, sophisticated, and often opaque nature. To remedy problems of lack of transparency in capital markets, financial regulation traditionally subjects regulated entities to certain reporting requirements. In applying the same remedy to solve opacity problems in ML-based trading, we may however encounter some significant challenges.

One idea often suggested is to grant regulators access to the AI code. This proposal is based on the basic assumption that by disclosing the programming code underlying a given ML model or system, the competent authority would be able to ascertain compliance with applicable legal and regulatory requirements.[981] In principle, 'opening the black box' may allow financial regulators to gain useful insights about ML functioning, investigating the models and the parameters bridging data input with output.[982] However, this approach assumes that regulators possess the necessary domain knowledge to make sense of greater access to information on the AI inner functioning. But this is something that is highly debatable given several constraints of both a practical, normative, and functional nature.[983] For instance, investment firms may value secrecy and thus hesitate to disclose proprietary details, fearing intellectual

981 *See generally* Miriam C Buiten, 'Towards Intelligent Regulation of Artificial Intelligence' (2019) 10(1) European Journal of Risk Regulation 41, 47-49 <https://doi.org/10.1017/err.2019.8> accessed 17 July 2024.

982 In the US, for instance, Regulation AT, if passed, would have opened algorithmic traders' source code to inspection by financial supervisors. *See, e.g.*, Woodward (n 276), which discusses the approaches implemented by both US and EU financial regulators to pursue transparency in algorithmic trading.

983 *See* Thomas Wischmeyer, 'Artificial Intelligence and Transparency: Opening the Black Box' in Thomas Wischmeyer and Timo Rademecher (eds), *Regulating Artificial Intelligence* (Springer Cham 2020) 79-87 <https://doi.org/10.1007/978-3-030-32361-5_4> accessed 17 July 2024; *see also* Allen (n 277) 198-199; Zetzsche and others (n 624) 48-49; Patricia Gomes Rêgo de Almeida, Carlos Denner dos Santos, and Josivania Silva Farias, 'Artificial Intelligence Regulation: A Framework for Governance' (2021) 23 Ethics and Information Technology 505, 507 <https://doi.org/10.1007/s10676-021-09593-z> accessed 17 July 2024.

property and competition issues.[984] Therefore, 'opening the black box' is *per se* a somewhat problematic policy option because, as a side effect, it may ultimately undermine trust, innovation, and competition.

Other less-intrusive approaches are emerging to safeguard adequate levels of transparency in ML-based systems, making XAI a fundamental field of interdisciplinary research in ML.[985] XAI entails technical solutions to provide actionable insights through explanations relating to the unique knowledge needs of interested stakeholders.[986] Importantly, a growing number of XAI applications are being researched also within the 'Deep Computational Finance' community.[987] In particular, XAI solutions are proposed to enhance transparency of complex ML-based trading applications allowing, including those allowing to establish autonomous trading agents (i.e., thanks to DRL methods).[988] By advancing the understanding, trust, and management of AI-generated outcomes, XAI can contribute to 'responsible AI' by

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984 *E.g.*, Iain Sheridan, 'MiFID II in the Context of Financial Technology and Regulatory Technology' (2017) 12(4) Capital Markets Law Journal 417, 420-421 <https://doi.org/10.1093/cmlj/kmx038> accessed 17 July 2024.

985 *See, e.g.*, footnote n. 270; Patrick Weber, K Valerie Carl, and Oliver Hinz, 'Applications of Explainable Artificial Intelligence in Finance – A Systematic Review of Finance, Information Systems, and Computer Science Literature' (2023) Management Review Quarterly 1 <https://doi.org/10.1007/s11301-023-00320-0> accessed 17 July 2024.

986 *See, e.g.*, Philippe Bracke and others, 'Machine Learning Explainability in Finance: An Application to Default Risk Analysis' (2019) Bank of England Staff Working Paper No. 816, 2 <https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2019/machine-learning-explainability-in-finance-an-application-to-default-risk-analysis.pdf> accessed 17 July 2024.

987 While XAI is an emerging field in ML research, there is a greater number of publications in the field of 'Deep Computational Finance' exploring various XAI solutions applicable to the financial trading domain. Some examples include, for instance: Mao Guan and Xiao-Yang Liu, 'Explainable Deep Learning for Portfolio Management: An Empirical Approach' in *ICAIF '21: Proceedings of the Second ACM International Conference on AI in Finance* (ACM 2022), Article 50 <https://doi.org/10.1145/3490354.3494415> accessed 17 July 2024; Satyam Kumar, Mendhikar Vishal, and Vadlamani Ravi, 'Explainable Reinforcement Learning on Financial Stock Trading Using SHAP' (2022) arXiv preprint 1 <https://doi.org/10.48550/arXiv.2208.08790> accessed 17 July 2024; Henry Han, Jeffrey Yi Lin Forrest, and Jiacun Wang, 'Explainable Machine Learning for High-Frequency Trading Dynamics Discovery' (2022) SSRN preprint 1 <https://ssrn.com/abstract=4256777> accessed 17 July 2024.

988 *Cf.* Heuillet, Couthouis and Díaz-Rodríguez (n 278).

creating systems that prioritise transparency, which in turn safeguard accountability.[989] It is however important to note that XAI tools, just like the AI systems they intend to elucidate, should adhere to established technical standards and may require being subject to auditing and certification by competent authorities. Without such scrutiny, there is a potential for subjecting opaque AI systems to explanations by other opaque systems, resulting in a cascade of black boxes, akin to the creation of a set of nested Matryoshka dolls.[990]

A lack of understanding in AI-powered algorithmic trading can lead to adverse consequences for model performance, risk evaluation, and management.[991] Opacity in the ML can cause unintended consequences, up to and including loss of control over AI trading systems. This can result in market misconduct and harm, making it crucial to understand how AI trading decisions are reached.[992] Nevertheless, the quest for interpretability[993] in ML can sometimes conflict with the pursuit of accuracy, posing a tough trade-off. Striking the right balance between transparency and accuracy is however crucial to ensure the viability of AI systems in complex and risky domains such as trading in capital markets. For some, this trade-off represents a misconception,

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989 *E.g.*, Adadi and Berrada (n 264) 52142.

990 *Cf.* Maliheh Ghajargar and Jeffrey Bardzell, 'Making AI Understandable by Making it Tangible: Exploring the Design Space with Ten Concept Cards' in Penny Sweetser and others (eds), *OzCHI '22: Proceedings of the 34th Australian Conference on Human-Computer Interaction* (ACM 2022) 78 <https://doi.org/10.1145/3572921.3572942> accessed 17 July 2024.

991 *E.g.*, Söhnke M Bartram, Jürgen Branke, and Mehrshad Motahari, 'Artificial Intelligence in Asset Management' (2021) CFA Institute Research Foundation, 26 <https://www.cfainstitute.org/-/media/documents/book/rf-lit-review/2020/rflr-artificial-intelligence-in-asset-management.pdf> accessed 17 July 2024.

992 *See* discussion in Chapter 2.5.B. *See also* Niklas Bussmann and others, 'Explainable Machine Learning in Credit Risk Management' (2021) 57 Computational Economics 203, 214 <https://doi.org/10.1007/s10614-020-10042-0> accessed 17 July 2024, who however discuss issues of ML opacity and associated risks in the context of credit risk management.

993 *See* Rosenfeld and Richardson (n 271), which provide a review of relevant literature and discuss different types of approaches/tools for interpretability in ML; *see also* Rudin and others (n 274), defining 'interpretable ML' as a '*model [that] obeys a domain-specific set of constraints to allow it (or its predictions, or the data) to be more easily understood by humans*.'

arguing that making black box AI explainable may not always be the optimal solution, and therefore propose a paradigm shift towards inherently interpretable ML models for high-stake decision-making.[994] Without claiming to determine which approach is best in this dissertation, it is nonetheless possible to argue that addressing the causes of opacity in ML is a fundamental requirement for promoting trust and regulatory compliance in AI trading.

D. Control frameworks and testing

Other regulatory measure may help deal with the complexity introduced by AI trading, particularly due to a lack of explainability associated with certain ML methods. These measures include technical solutions such as robust control frameworks (i.e. risk-control, regulatory compliance, real-time monitoring, and market abuse surveillance) as well as the testing of algorithms prior to implementation.[995]

To ensure the integrity of financial markets, the auditing of AI trading systems, both before and after their deployment in markets, appears a fundamental measure of governance. By subjecting AI trading to testing exercises under various market settings and conditions, potential abusive behaviours such as market manipulation might be identified and so prevented *ex-ante*. Although a testing regime already exist under MiFID II, testing frameworks may need to be recalibrated as part of a new authorisation regime specifically designed for AI trading that is powered by ML.[996] Given the challenges that competent authorities may face in checking for compliance with testing requirements, an independent third-party organisation may be better positioned to

[994] *See* Rudin (n 275); *see also* Rudin (n 274), discussing a number of technical challenges in interpretable ML, including in the context of RL methods.

[995] *See, e.g.*, AFM (n 105) 14. However, it is worth reiterating that existing regulatory regimes already mandate investment firms to have appropriate control systems in place and to conduct both behavioural and conformance testing of their trading systems as market access rule. Nevertheless, the sophistication in ML methods and related trading strategies may require more stringent requirements according to the risks posed by specific applications.

[996] *E.g.*, Allen (n 277) 196-198.

take on this responsibility. An *ad-hoc* established body to oversee algorithmic testing could, on the one hand, ensure the technical expertise necessary for effective scrutiny of the behaviour of trading algorithms employed by market players and, on the other hand, by guaranteeing its institutional independence, ensure the protection of the interests of the various stakeholders involved.[997]

The institutionalisation of stricter, more in-depth defined testing regimes, however, requires thoughtful considerations regarding the very scope of testing activity, as the success of the testing procedures will determine the authorisation to use specific AI-powered systems and/or strategies.[998] In other words, having successfully passed testing, AI system would be certified against known forms of market abuse—i.e. 'good market conduct by design'—and thus allowed to operate in the markets. However, fundamental decisions will have to be made regarding the exact scope of testing framework for auditing ML methods, including specific requirements on human role and responsibility within the AI lifecycle (e.g., covering aspects of accountability, liability, oversight, and regulatory compliance, etc.), transparency about the functioning and behaviour of AI systems (e.g., interpretability/explainability, documentation, etc.), as well as the role of training data employed in the simulated scenarios leading to certification.

Authorisation requirements should, however, be calibrated on a proportional and risk-based approach, tailoring them to concrete use cases considering the capability of given AI-powered trading systems, specific market structures, and trading dynamics to assess the likelihood to result in manipulative outcomes and behaviours. Still, questions remain on how the potential of AI to misbehave can be effectively observed, measured, and ascertained, particularly in the face of sophisticated

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997 *See, e.g.*, Andrew Tutt, 'An FDA for Algorithms' (2017) 69(1) Administrative Law Review 83, 104-111 <http://www.administrativelawreview.org/wp-content/uploads/2019/09/69-1-Andrew-Tutt.pdf> accessed 17 July 2024, advocating the creation of a centralised regulatory agency responsible for regulating various aspects relating to the governance of AI.

998 *See, e.g.*, Cartea and others (n 345); Barr and others (n 344).

manipulative strategies such as, for instance, ‘aggressive’ cross-asset and cross-market trading, or even ‘tacit’ forms of collusion. In general, a clear and robust theoretical framework is required to effectively discern between legitimate and unlawful trading practice. To be effective, such a framework must be based on the best available scientific knowledge and a proper understanding of market structure and functioning,[999] but also about the technological aspects related to AI trading. In particular, with regard to risks of collusive behaviours, this framework also requires to clearly define, from a computational economics perspective, what is meant by non-competitive behaviour between rival AI trading agents.[1000]

Mitigating the risks of misconduct by AI trading through measures to audit the functioning of algorithms and surveillance of their behaviour in markets, however, constitutes a complex challenge to address. Although pre-approval testing can help uncover market manipulation risks associated with specific ML applications, it presents a number of both methodical and practical uncertainties. After all, there can be significant differences between laboratory/testing facilities and real-world environments, which can ultimately invalidate the overall effectiveness of testing as an auditing procedure.[1001]

Despite these challenges, however, the fact that among competent authorities, there are those who are exploring innovative solutions to improve their regulatory and supervisory capabilities, including the use of SupTech tools as reviewed in Chapter 7, should be viewed positively. Using AI to supervise AI seems to an interesting promise,

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999 *See, e.g.*, Donald (n 783), arguing that to effectively regulate market manipulation, regulators must first have a clear and correct understanding of markets and the price creation mechanism.

1000 *See generally* Harrington (n 397) 356-358, developing a three steps theoretical framework to help regulators determine the lawfulness of market conduct of algorithms.

1001 *Cf.* Allen (n 277) 200-201; BoE and FCA (n 241) 37-38; AFM (n 105) 14-15 and 17; Ellen P Goodman and Julia Trehu, ‘Algorithmic Auditing: Chasing AI Accountability’ (2023) 39(3) Santa Clara High Technology Law Journal 289, 320-330 <https://digitalcommons.law.scu.edu/chtlj/vol39/iss3/1> accessed 17 July 2024, which provide an overview of the challenges and potential limitations generally encountered by algorithmic auditing frameworks.

if not a necessary one.[1002] Nevertheless, the recourse to ML-based methods by regulators and supervisors, as well as by independent testing bodies, must be supported by a sound theoretical basis and access to reliable and representative training data to ensure effective auditing of AI trading behaviour and understanding of its effect on markets.[1003] Indeed, without a sound scientific basis, testing frameworks could become haphazard and meaningless exercises and even fail to detect those risky AI trading strategies that may jeopardise the integrity and stability of markets.

E. From traditional 'command and control' to 'dynamic regulation'

The scholarly debate on AI governance, both pertaining to the financial sector as well as other domains, gives rise to divergent perspectives and visions.[1004] On the one hand, certain scholars contend that existing legal frameworks are adequate to ensure the effective governance of risks associated with AI trading. Under this perspective, they argue that introducing novel regulatory measures remains unwarranted, especially considering the inherent uncertainty surrounding the additional risks introduced by AI. In their view, any AI-targeting regulation could potentially hinder the benefits linked to technological innovation. According to this line of reasoning, thus, whenever feasible, market-driven solutions, although temporary in nature, should be prioritised

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1002 *E.g.*, Lawrence G Baxter, 'Adaptive Financial Regulation and RegTech: A Concept Article on Realistic Protection for Victims of Bank Failures' (2016) 66 Duke Law Journal 567, 600-603 <https://scholarship.law.duke.edu/dlj/vol66/iss3/5> accessed 17 July 2024; Allen (n 277) 203-205; Coglianese and Lai (n 397).

1003 *See, e.g.*, Laurent Dupont, Olivier Fliche, and Su Yang, 'Governance of Artificial Intelligence in Finance' (June 2020) Discussion Document, ACPR, Banque de France, 4 and 34-35 <https://acpr.banque-france.fr/sites/default/files/medias/documents/20200612_ai_governance_finance.pdf> accessed 17 July 2024; Gérard Hertig, 'Using Artificial Intelligence for Financial Supervision Purposes (1 February 2021) Future Resilient Systems No. 4, 4-7 <https://ethz.ch/content/dam/ethz/special-interest/dual/frs-dam/documents/Hertig%20WP%20AI%20and%20Financial%20Supverision%20(Feb-1-2021).pdf> accessed 17 July 2024.

1004 *See generally* Araz Taeihagh, 'Governance of Artificial Intelligence' (2021) 40(2) Policy and Society 137, 143-148 <https://doi.org/10.1080/14494035.2021.1928377> accessed 17 July 2024.

and even endorsed by regulatory bodies.[1005] The rationale behind this approach lies in the belief that self-regulatory mechanisms, when applied to the governance of innovative technologies, often materialise more swiftly than formal regulations instituted by regulators. Moreover, this strategy allows for a pragmatic response: should industry-driven self-regulation prove inadequate, it retains the flexibility to pave the way for regulatory interventions when distinct challenges necessitating precise actions come to the fore.[1006]

Conversely, at the opposite end of the spectrum, certain scholars advocate for a revision of existing regulation, asserting that current governance frameworks are struggling to keep pace with the rapid advances in AI, particularly its subfield of ML. This dissertation aligns with the latter viewpoint, contending that the optimal path forward is to adopt innovative regulatory approaches to enhance the effectiveness of AI governance, especially in light of the emerging limitations evident in current regulatory frameworks for algorithmic trading. In particular, we delve below into the advantages of embracing innovative regulatory paradigms that can swiftly accommodate and adapt to rapid technological advances, often referred to as 'dynamic' or 'adaptive' regulation by certain legal scholars.[1007]

i. Innovative modes of regulation

Our starting point, however, is the recognition of the growing constraints faced by conventional 'command-and-control' regulatory approaches when addressing

[1005] *See, e.g.*, Eren Kurshan, Hongda Shen, and Jiahao Chen, 'Towards Self-Regulating AI: Challenges and Opportunities of AI Model Governance in Financial Services' *ICAIF '20: Proceedings of the First ACM International Conference on AI in Finance, October 2020* (ACM 2021) Article 49 <https://doi.org/10.1145/3383455.3422564> accessed 17 July 2024.

[1006] *See, e.g.*, Reed, Kennedy, and Nogueira Silva (n 707) 31.

[1007] *Cf.* Baxter (n 1002); Mark Fenwick, Wulf A Kaal, and Erik PM Vermeulen, 'Regulation of Tomorrow: What Happens When Technology is Faster than the Law?' (2017) 6(3) American University Business Law Review 561 <https://digitalcommons.wcl.american.edu/aublr/vol6/iss3/1> accessed 17 July 2024; Lo (n 329).

challenges stemming from cutting-edge technologies. These limitations stem from various factors, such as, for instance, the increasing information asymmetry between regulatory bodies and entities subject to regulation. This asymmetry is often due to the complexity and opacity of AI trading in the presence of specific ML methods. Hence, the concept of 'adaptive regulation', integrating both *ex-ante* and *ex-post* regulatory measures, presents a potentially more effective approach to deal with the specificities of AI trading.[1008] On the one hand, *ex-ante* regulation is designed to prevent the occurrence of harmful conduct by elevating the standards of quality, safety, and reliability within AI applications. This can be achieved through a spectrum of measures, including but not limited to, requirements pertaining to transparency, explainability, data governance, quality assurance, human accountability, rigorous testing, and certification.[1009] On the other hand, *ex-post* regulation seeks to reinforce the effectiveness of *ex-ante* regulatory measures. It may encompass various strategies such as auditing protocols, control mechanisms, regulatory compliance, as well as enhanced reporting requirements to facilitate both supervision and law enforcement.[1010] In essence, an adaptive regulatory framework should be characterised by continuous evolution through regulatory experimentation, informed by both success and failures, thus ensuring its future validity in the face of a changing regulatory environment. This adaptation necessitates rigorous monitoring by regulators and the meticulous documentation of both shortcomings and achievements within the regulatory landscape.

1008 *E.g.*, Allen (n 277) 195-196; Gina-Gail S Fletcher, 'Macroeconomic Consequences of Market Manipulation' (2020) 83 Law and Contemporary Problems 123, 138-140 <https://scholarship.law.duke.edu/lcp/vol83/iss1/8> accessed 17 July 2024.

1009 *See, e.g.*, Allen (n 277) 196-201; *see also* Gianclaudio Malgieri and Frank Pasquale, 'From Transparency to Justification: Toward *Ex Ante* Accountability for AI' (2022) Brussels Privacy Hub Working Paper Vol. 8 No 33 <https://brusselsprivacyhub.com/wp-content/uploads/2022/05/BPH-Working-Paper-vol8-N33.pdf> accessed 17 July 2024, advancing the idea that 'high-risk' AI applications should, until proven otherwise, be subject to a regime of "unlawfulness by default".

1010 *E.g.*, Allen (n 277) 203.

Hence, considering the kaleidoscopic behaviour of AI trading systems equipped with self-learning capabilities thanks to ML, recourse to *ex-post* regulatory measures becomes necessary in mitigating some of the limitations inherent in *ex-ante* regulatory instruments. Since the effectiveness of the latter can be constrained by the inability to address the dynamic and evolving market behaviour of ML-powered systems, they necessitate complementary measures. In this context, the implementation of comprehensive documentation and reporting frameworks emerges as valuable tools to implement *ex-post* regulatory measures, furnishing regulatory authorities with timely insights into the specific trading strategies, including the underlying operational processes, employed by market participants leveraging advanced AI trading applications.[1011] Additionally, the emerging area of RegTech presents a promising avenue for forging closer ties between the need of financial regulators and the interests of the entities they oversee. For example, emerging initiatives explore the potential of introducing machine-readable regulation as an augmentation to existing regulatory tools.[1012] This innovative approach has the potential to facilitate direct interaction between financial authorities and the AI trading systems employed by market participants. By directly feeding conduct rules into their computational systems, AI systems could thus be guided towards lawful conduct, thereby enhancing the effectiveness of both regulatory compliance and market conduct supervision.

1011 *Cf.* ibid 203; Fletcher (n 71) 542-543.

1012 *See, e.g.*, FINRA (n 837) 9, reporting that financial regulators are actively exploring and adopting the concept of 'machine-readable' rulebooks, which, arguably, could empower organisations to automate their internal processes of regulatory compliance; Schwalbe (n 424) 599, proposing the concept of integrating legal provisions and constraints directly into algorithms, akin to the three robotics laws conceptualised by Isaac Asimov; *but see* Eva Micheler and Anna Whaley, 'Regulatory Technology: Replacing Law with Computer Code' (2020) 21 European Business Organization Law Review 349, 362-364 <https://doi.org/10.1007/s40804-019-00151-1> accessed 17 July 2024, arguing, however, that there might be potential obstacles to the effective integration of RegTech solutions for deploying 'machine-readable' code into current IT systems. Additionally, the authors emphasise the possible occurrence of risks of regulatory capture associated with future developments in RegTech projects.

Furthermore, as mentioned earlier, another innovative regulatory instrument may soon lie in technological innovations aimed at ensuring and promoting adequate levels of transparency in AI systems. Indeed, the field of XAI, dedicated to researching technical solutions designed to elucidate the inner workings of opaque AI systems, thus making them intelligible and accessible to a wide array of stakeholders.[1013] By facilitating improved predictability, enhanced control, streamlined regulatory compliance, and robust oversight, advancements in XAI holds the potential to bolster trust in AI adoption, including within the financial trading industry.[1014]

Overall, the governance of risks stemming from innovative and transformative technologies like AI, particularly in the contest of ML-powered in financial trading, necessitates innovative regulatory approaches. However, prior to delving into an exhaustive examination of potential enhancements to the existing regulatory frameworks, we propose to examine the prevailing policy trends in the area of AI governance in the financial industry. As will be seen, although ethical-legal issues arising from the integration of AI into society have attracted increasing attention from policymakers and various industry regulators alike, a significant overhaul of regulatory frameworks for algorithmic trading does not appear to be on the immediate horizon.

8.3 Regulatory and Policy Trends in AI Governance in Finance

After providing an overview of emerging legal theories on AI regulation, this section shifts the focus to current policy initiatives for AI governance. Mindful of the limitations in providing an exhaustive examination of the swiftly evolving landscape of AI policy and law, the main objective is to highlight key developments that may have implications for the financial sector.

1013 See footnote n. 985.

1014 *See* footnote n. 270.

As we shall see, in closely monitoring market-driven advancements in AI within the financial industry, financial regulators typically adopt a 'wait-and-see' approach. Only where regulators play a more proactive role in AI regulation, have they so far been limited to promoting guiding principles aimed at ensuring safe and responsible AI adoption by industry players. Without any notable exceptions, these initiatives focus primarily on mitigating risks to end consumers. Indeed, very little guidance—if any—has so far been extended to the capital markets trading sector, particularly in the area of proprietary trading.

To better understand all these developments, the remainder of this section will review (A) general trends in the area of AI law and policy worldwide and, more specifically, (B) initiatives targeting AI adoption in the financial sector.

A. General trends in AI law and policy

At both supranational and national levels, public institutions worldwide actively engage in lively policy debates on AI governance and regulation.[1015] Motivated by a growing awareness of the intrinsic risks and opportunities associated with AI adoption, encompassing economic, societal, and geopolitical dimensions, these stakeholders proceed thoughtfully to chart the most optimal pathways for effective AI governance. Thus, to discern potential implications for the financial trading domain, below we explore some of the most significant policy developments: (i) at the international level, focusing on the case of the OECD, and (ii) at the national and regional level, with a primary lens on the EU. This overview will also serve to reflect on (iii) the importance of a cohesive and coherent global approach towards AI governance.

[1015] For an analysis of the current state of global AI governance, see Lewin Schmitt, 'Mapping Global AI Governance: A Nascent Regime in a Fragmented Landscape' (2022) 2 AI and Ethics 303 <https://doi.org/10.1007/s43681-021-00083-y> accessed 17 July 2024; Simon Chesterman and others, 'The Evolution of AI Governance' (2023) TechRxiv preprint 1 <https://doi.org/10.36227/techrxiv.24681063.v1> accessed 17 July 2024.

i. International level

At the international level, it is possible to observe the flourishing of numerous initiatives aiming to establish a global framework for AI governance. These initiatives, mainly representing high-level guidelines and soft law instruments, serve at least a twofold purpose. On the one hand, they aim to raise awareness among various stakeholders about AI governance challenges. On the other, recognising AI adoption as a global concern with far-reaching implications, these initiatives seek to promote a consistent approach among global policymakers. With the focus to inform future AI policy and regulation, the goal is to prevent a race to the bottom in AI governance and mitigate the risks of regulatory fragmentation across jurisdictions.[1016]

Within this policy space, the work of the OECD, whose institutional goal is to serve as a platform for governments to work together to find solutions to common problems in order to improve general economic and social well-being, deserves at least a mention. One of the earliest global developments in AI policy, indeed, is the 2019 OECD Recommendation on AI. This landmark instrument of soft law outlines a policy framework intended for adoption by both public and private organisations, providing guidance in the forms of high-level principles for a human-centric approach to trustworthy AI adoption.[1017] While the OCED AI principles have been endorsed by the vast majority of governments worldwide, uncertainties persist concerning their effective and consistent enforcement.[1018] Given the somewhat abstract and non-

[1016] *See, e.g.*, Schmitt (n 1015) 309-311.

[1017] The OECD framework promotes five key principles, including (i) the promotion of inclusive growth, sustainable development, and well-being, (ii) a commitment to human-cantered values and fairness, (iii) the pursuit of transparency and explainability, (iv) the pursuit of robustness, security and safety, and (v) the endorsement of human accountability. *See* OECD, 'Recommendation of the Council on Artificial Intelligence' (2019) OECD/LEGAL/0449 <https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449> accessed 17 July 2024.

[1018] For in-depth comparative research, providing a comprehensive perspective on the evolution of AI law and policy across 75 countries worldwide, see Center for AI and Digital Policy (CAIDP), *Artificial Intelligence and Democratic Values Index* (CAIDP 2023) <https://www.caidp.org/app/download/8452735863/AIDV-Index-2022.pdf> accessed 17 July 2024. The CAIDP's report also include an assessment of how various countries have endorsed and binding nature of the OCED AI principles, their effectiveness ultimately depends on the willingness of the various stakeholders to voluntarily adopt and commit to them. In addition, the presence of effective oversight and enforcement mechanisms will also prove crucial. As a result, it is unclear whether and to what extent these principles alone can actually contribute to ensuring and advancing AI governance, particularly in the area of financial trading.[1019]

Overall, the OECD undoubtedly emerges as key platform for promoting discussion among world leaders on AI governance, as evidenced, for example, by its recent contribution to the Hiroshima AI Process in which G7 leaders addressed the issue of responsible and safe AI adoption.[1020]

ii. National and regional level

At the national and regional level, recognising the importance of AI and its profound implications for their economies and societies, several governments have formulated strategies and policies dedicated to AI.[1021] These multifaceted policy endeavours typically encompass commitments to (i) invest in AI research and development,

implemented the OECD AI Principles. Nevertheless, the OECD itself recently produced a report that maps the implementation of its principles by governments. *See* OECD, 'The State of Implementation of the OECD AI Principles Four Years On' (2023) OECD Artificial Intelligence Papers No. 3, October 2023 <https://doi.org/10.1787/dee339a8-en> accessed 17 July 2024.

[1019] For critical accounts on the role of soft law to ensure effective AI governance, see generally Craig E Shank, 'Credibility of Soft Law for Artificial Intelligence—Planning and Stakeholder Considerations' (2021) 40(4) IEEE Technology and Society Magazine 25 <https://doi.org/10.1109/MTS.2021.3123737> accessed 17 July 2024.

[1020] *See* OECD, 'G7 Hiroshima Process on Generative Artificial Intelligence (AI): Towards a G7 Common Understanding on Generative AI' (2023) Report Prepared for the 2023 Japanese G7 Presidency and the G7 Digital and Tech Working Group (OECD Publishing, 7 September 2023) <https://www.oecd-ilibrary.org/docserver/bf3c0c60-en.pdf> accessed 17 July 2024. The reader can monitor the OECD's work on AI law and policy at the webpage: <https://www.oecd.org/digital/artificial-intelligence> accessed 17 July 2024.

[1021] For a comparative overview of emerging national policies and strategies worldwide, see CAIDP (n 1018).

promoting AI adoption across industries and government sectors, (ii) bolster academic research capability, and (iii) facilitate fruitful multi-stakeholder collaboration on AI.[1022]

Importantly, governments are placing significant emphasis on nurturing AI talent and education. This include initiatives such as scholarships, training programs, research grants, and the cultivation of highly qualified professors and research personnel to bolster the growth of AI expertise within both publicly-funded academia and the private sectors.[1023] At the same time, governments, alongside other stakeholders—like academia, civil society, but also private organisations—express a general concern about the potential risks associated with AI adoption, particularly with regard to ethical and legal considerations as well as the general impact of AI on the well-being of society.[1024]

Overall, government policy initiatives are mainly designed to harness the vast potential benefits of AI technology while mitigating its associated risks and challenges. These efforts are geared towards ensuring that AI development, deployment, and use aligns harmoniously with societal values, ultimately benefiting all segments of society. Whit all this in mind, we now turn to take a closer look at ongoing regulatory initiatives within the EU, whose upcoming AI legislation is considered by many observers to be one of the most significant developments to date in the field.

1022 *See generally* Tahereh Saheb and Tayebeh Saheb, 'Topical Review of Artificial Intelligence National Policies: A Mixed Method Analysis' (2023) 74 Technology in Society, Article 102316, 10-11<https://doi.org/10.1016/j.techsoc.2023.102316> accessed 17 July 2024.

1023 *See, e.g.*, ibid 4.

1024 *See, e.g.*, AI Safety Summit (n 23); *see also* Kiran Stacey and Dan Milmo, 'UK, US, EU and China Sign Declaration of AI's 'Catastrophic Danger' (*The Guardian*, 1 November 2023) <https://www.theguardian.com/technology/2023/nov/01/uk-us-eu-and-china-sign-declaration-of-ais-catastrophic-danger> accessed 17 July 2024.

- The EU AI Act

As one of the most significant developments in AI regulation, the EU AI Act represents "the world's first comprehensive AI law."[1025] Initially proposed in April 2021 by the European Commission, the AI Act has undergone an extensive process of political debate and negotiation culminating in the December 2023 agreement between the European Parliament and the European Council.[1026] After over three years of discussions, revisions, and adjustments to address evolving AI-related market developments, the AI Act was formally adopted by the European Council on 21 May 2024.[1027]

In essence, the AI Act is proposed as a comprehensive legislation governing AI systems employed within the EU. It aims to strike a balance between fostering innovation and ensuring effective safeguards by preventing the deployment of systems that pose risks to the health, safety, and fundamental rights of EU citizens.[1028] The AI Act entails a risk-based regulatory approach based on the pyramid of criticality posed by AI applications.[1029] Relatedly, AI applications are categorised according to risk

1025 European Parliament, 'EU AI Act: First Regulation on Artificial Intelligence' (14 June 2023) <https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence> accessed 17 July 2024.

1026 European Parliament, 'Artificial Intelligence Act: Deal on comprehensive Rules for Trustworthy AI' (9 December 2023) Press Release <https://www.europarl.europa.eu/news/en/press-room/20231206IPR15699/artificial-intelligence-act-deal-on-comprehensive-rules-for-trustworthy-ai> accessed 20 June 2024; European Council, 'Artificial Intelligence Act: Council and Parliament Strike a Deal on the First Rules for AI in the World' (9 December 2023) Press Release 986/23 <https://www.consilium.europa.eu/en/press/press-releases/2023/12/09/artificial-intelligence-act-council-and-parliament-strike-a-deal-on-the-first-worldwide-rules-for-ai/pdf> accessed 17 July 2024.

1027 European Council, 'Artificial Intelligence (AI) Act: Council Gives Final Green Light to the First Worldwide Rules on AI' (21 May 2024) <https://www.consilium.europa.eu/en/press/press-releases/2024/05/21/artificial-intelligence-ai-act-council-gives-final-green-light-to-the-first-worldwide-rules-on-ai> accessed 20 June 2024.

1028 *See* AI Act recital (1).

1029 *See, e.g.*, Mauritz Kop, 'EU Artificial Intelligence Act: The European Approach to AI' (2021) Stanford-Vienna Transatlantic Technology Law Forum, Transatlantic Antitrust and IPR profiles in relation to their intended use and technical functioning. Generally, higher-risk AI systems are subject to more stringent obligations. Without claiming to be exhaustive, regulatory requirements for 'high-risk' AI systems cover several critical areas, including risk management, data governance, technical documentation, record-keeping, transparency towards deployers, human oversight, and ensuring technical robustness, accuracy and safety.[1030] These obligations are further reinforced by specific provisions mandating ongoing monitoring by deployers and post-market monitoring by providers.[1031] Notably, Annex III of the AI Act outlines a non-exhaustive list of 'high-risk' AI systems that are subject to stricter regulatory requirements.[1032] Although the AI Act does not explicitly address AI applications in financial services, it does classify AI-powered credit scoring—whether conducted by public or private entities—as a 'high-risk' application.[1033] By contrast, AI systems that do not meet the criteria for 'high-risk' classification are subject to less stringent obligations, primarily concerning transparency measures such as use disclosure and adherence to voluntary codes of conduct.[1034]

Given the diverse risks posed by different AI applications in finance, as demonstrated throughout this dissertation, a risk-based regulatory approach seems well-suited to address the nuances of ML-powered trading systems. However, given its specific objectives, the applicability of the AI Act to algorithmic trading remains highly

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Developments, Stanford University 1 <https://law.stanford.edu/publications/eu-artificial-intelligence-act-the-european-approach-to-ai> accessed 17 July 2024.

1030 *See* AI Act artt 6-18.

1031 *See* AI Act art 26(5) (on 'monitoring obligations for deployers of high-risk AI systems') and art 72 (on 'post-market monitoring by providers').

1032 *See* AI Act Annex III.

1033 *E.g.*, Wojtek Buczynski, 'The EU Artificial Intelligence Act and Financial Services' (*CFA Institute Blog*, 6 April 2022) <https://blogs.cfainstitute.org/investor/2022/04/06/the-eu-artificial-intelligence-act-and-financial-services> accessed 17 July 2024.

1034 *See* AI Act art 50 (on 'transparency obligations for providers and deployers') and art 95 (on 'codes of conduct').

ambiguous, if not entirely lacking. This piece of legislation, in fact, does not explicitly account for the specific risks associated with AI-based technology in financial trading, which are predominantly economic in nature (i.e. financial losses) and, as such, do not directly threaten fundamental rights.[1035] While the AI Act clearly extends to consumer-facing financial services—where issues such as discriminatory credit scoring or biased financial advice can significantly impact consumers' fundamental rights—its relevance to the domain of algorithmic trading appears, at best, speculative and prospective.

Despite these uncertainties, a risk-based regulatory approach offers a valuable conceptual framework for addressing the unique challenges posed by AI trading systems based on their associated risks. We will return to this point later in this chapter. For now, suffice it to say that the AI Act represents an innovative model for AI governance and regulation, with the potential to inspire similar initiatives in other jurisdictions and on a global scale.[1036]

iii. Risks of regulatory fragmentation

Despite some common policy trends, however, there is a risk that different jurisdictions will endow themselves with different AI governance priorities and models.[1037] But this

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[1035] For a critical account on the scope of application of the EU AI Act to financial services, see Antonella Sciarrone Alibrandi, Maddalena Rabitti, and Giulia Schneider, 'The European AI Act's Impact on Financial Markets: From Governance to Co-Regulation' (2023) European Banking Institute Working Paper Series 2023 – no. 138, 7 and 16 <https://ssrn.com/abstract=4414559> accessed 17 July 2024.

[1036] Indeed, it can be argued that the EU AI Act proposal anticipated, if not triggered, the policy debate on AI regulation across other jurisdictions. One notable example is represented by Canada and its proposed AI legislation under Bill C-27. *See* House of Commons of Canada, 'Bill C-27: An Act to enact the Consumer Privacy Protection Act, the Personal Information and Data Protection Tribunal Act and the Artificial Intelligence and Data Act and to make consequential and related amendments to other Acts', First reading, June 16, 2022, 91102 <https://www.parl.ca/Content/Bills/441/Government/C-27/C-27_1/C-27_1.PDF> accessed 17 July 2024. Similarly, other important jurisdictions, like China, Japan, Korea, Singapore, the UK, and the US are all somewhat following a risk-based approach to AI regulation. *See* Ernst & Young, 'The Artificial Intelligence (AI) Global Regulatory Landscape: Policy Trends and Considerations to Build Confidence in AI' (September 2023) 5 <https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/ai/ey-the-artificial-intelligence-ai-global-regulatory-landscape.pdf> accessed 17 July 2024.

[1037] For a systematic examination of national AI strategies, along with a categorisation based on distinct AI governance approaches and priorities, see Gleb Papyshev and Masaru Yarime, 'The State's Role in Governing Artificial Intelligence: Development, Control, and Promotion Through National Strategies' divergence could lead to fragmented or even conflicting policy frameworks due to various contextual factors such as geopolitical considerations, political ideologies, and economic interests, among others.[1038] Such fragmentation may, in turn, pose a tangible threat to the formation of a global consensus on the optimal approach to AI governance and regulation. As a result of this fragmentation, risks of a race to the bottom may emerge in safe and responsible AI adoption by both public and private organisations. Whenever this is the case, regulatory fragmentation may ultimately undermine the fundamental principle that AI should be truly human-centred and at the service of the whole society.[1039]

Given the absence of a global regulatory authority, the risks associated with fragmented AI regulation emphasise the necessity for coordinated global AI governance policies.[1040] Inconsistencies among national and regional regulations may indeed pose substantial challenges for firms adopting AI as well as for regulators

(2023) 6(1) Policy Design and Practice 79 <https://doi.org/10.1080/25741292.2022.2162252> accessed 17 July 2024.

[1038] *See* Rumtin Sepasspour, 'A Reality Check and a Way Forward for the Global Governance of Artificial Intelligence' (2023) 79(5) Bulletin of the Atomic Scientists 304, 306-309 <https://doi.org/10.1080/00963402.2023.2245249> accessed 17 July 2024; Lazard, 'Geopolitics of Artificial Intelligence' (October 2023) Research Brief No 175, 10 and 19 <https://lazard.com/media/cyenforc/lazard-geopolitical-advisory_geopolitics-of-artificial-intelligence_-oct-2023.pdf> accessed 17 July 2024, warning of the possible emergence of distinct regulatory ecosystems; *see also* Shekhar Aiyar and others, 'Geoeconomic Fragmentation and the Future of Multilateralism' (January 2023) IMF Staff Discussion Notes, SDN/2023/001 <https://www.imf.org/-/media/Files/Publications/SDN/2023/English/SDNEA2023001.pdf> accessed 17 July 2024, examining how the evolving geopolitical landscape may lead to a new multi-polar global order.

[1039] *Cf.* Amandeep S Gill and Stefan Germann, 'Conceptual and Normative Approaches to AI Governance for a Global Digital Ecosystem Supportive of the UN Sustainable Development Goals (SDGs)' (2022) 2 AI and Ethics 293 <https://doi.org/10.1007/s43681-021-00058-z> accessed 17 July 2024, advocating a globally coordinated approach to digital public goods for AI governance in order to ensure human-centred and beneficial AI adoption for global societies as a whole.

[1040] *See, e.g.*, Peter Cihon, Matthijs M Maas, and Luke Kemp, 'Fragmentation and the Future: Investigating Architectures for International AI Governance' (2020) 11(5) Global Policy 545 <https://doi.org/10.1111/1758-5899.12890> accessed 17 July 2024; Schmitt (n 1015); Matthew Hutson, 'Rules to Keep AI in Check: Nations Carve Different Paths for Tech Regulation: A Guide to How China, the EU, and the US Are Reining in Artificial Intelligence' (2023) 620 Nature 260, 263 <https://doi.org/10.1038/d41586-023-02491-y> accessed 17 July 2024.

striving to uphold public interests. Yet, in the context of capital markets, the global and cross-border nature of AI adoption and its implications for financial regulation cannot be ignored.

Hence, with these policy dynamics in mind and the conscious need to ensure consistent and cohesive regulation of AI in finance, we explore some of the most significant initiatives enabled by financial regulators in selected jurisdictions below. In particular, we analyse the strategies and instruments adopted for AI governance policies in this area.

B. The governance of AI in finance

As AI becomes increasingly integrated into financial firms' business processes and activities, the role of financial regulators in overseeing safe and responsible adoption takes centre stage. Regulatory agencies, in fact, face the challenging task of formulating an optimal strategy for ensuring effective AI governance and regulation. Particularly, the additional risks to markets introduced by AI trading underscores the necessity for robust governance and regulatory measures. To this end, further regulations may be required to ensure that the integration of AI-powered technology into financial trading adheres to legal principles and norms and societal core values.

In theory, a plethora of regulatory approaches can be considered. At opposite ends of the spectrum, one finds (i) the prudential, proactive strategies founded on the enactment of stringent hard-law regulations and, conversely, (ii) the lenient, laissez-faire approaches that delegate the creation of governance frameworks to industry participants or other stakeholders on a voluntary basis. Amidst this continuum, one can instead find, for example, soft law instruments issued by competent authorities, both internationally and nationally, as well as a variety of forms of collaboration among the various actors within the regulatory space—including policymakers, regulators, market participants, industry organisations, academia, civil society, etc.—in order to establish both regulatory and technical standards.[1041] Unfortunately, this is not the place to discuss in depth what is the best approach to regulating AI trading. Suffice it to point out that, unlike other segments of the financial sector, algorithmic trading has attracted limited regulatory interest in AI. In part, this might be justified because many jurisdictions already subject algorithmic trading to specific rules for technology governance, including market conduct rules.

Perhaps because the associated risks are more immediate to perceive by the public, some jurisdictions have only adopted soft law instruments particularly targeting consumer-facing AI applications in finance.[1042] Conversely, no major regulatory policy initiative has been taken across jurisdictions yet to tackle the additional uncertainty and incremental system complexity induced by AI, particularly ML, in financial trading.[1043] It is worth noting, however, that some financial regulators have started, at least, to explore the need to review and adjust existing regulatory frameworks to ensure the effective governance of AI trading, due to the technical specificities of ML methods and the associated additional risks to markets.[1044] Without venturing into major regulatory reforms yet, the bet of financial regulators is to promote best practices within the industry, incentivising market participants to effectively take due care of their algorithmic trading systems.[1045] In the author's view, this regulatory momentum should presents an opportunity for policymakers to explore

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1041 For a discussion of different modes of regulation applicable to AI governance, see generally Gillian K Hadfield and Jack Clark, 'Regulatory Markets: The Future of AI Governance' (2023) arXiv preprint 1, 12-18 <https://arxiv.org/abs/2304.04914> accessed 17 July 2024.

1042 *See* footnote n. 1035.

1043 As an important example, the EU's MiFID II has only just come into force in 2018 but, as some scholars (*see, e.g.*, Karremans and Schoeller (n 78))—including the present author—argue, may already show some regulatory inefficiency due to the increasing levels of sophistication achieved by algorithmic trading systems as a result of continued advances in ML methods.

1044 *Cf.* BoE and FCA IV (n 345); AFM (n 105).

1045 *See, e.g.*, BoE and FCA III (n 241), highlighting three crucial areas for safe and responsible AI adoption: (i) 'data', (ii) 'model risk', and (iii) 'governance'.

the potential benefits and challenges of regulating AI in finance and consider the most effective regulatory frameworks to adopt.

Below we (i) highlight some of the most significant developments in AI regulation in the financial sector, almost exclusively in the form of soft law legal instruments, and (ii) discuss one of the biggest challenges in AI governance, namely the translation of high-level, legal principles into actual technical and organisational solutions.

i. Emerging trends in the regulation of AI in finance

In an effort to ensure consumer protection and uphold market integrity, a number of governments and financial regulatory bodies have taken proactive steps to introduce soft law instruments to address aspects pertaining to AI risk and governance.

Representing one of the world's earliest endeavours to promote safe and responsible AI adoption in the financial sector, the Monetary Authority of Singapore (MAS) released the 'FEAT Principles' in November 2018. The FEAT framework emphasises the vital role of the principles of 'fairness', 'ethics', 'accountability', and 'transparency' to shape AI governance, thus ensuring trustworthy AI applications.[1046] More recently, in June 2023, MAS, in collaboration with a consortium of thirty-one industry players, launched the 'Veritas Toolkit version 2.0'[1047], a responsible AI toolkit to assist financial institutions in evaluating their compliance with the FEAT principles.[1048] Singapore's Veritas toolkit is complemented by the open-sourced 'AI

[1046] *See* MAS, 'Principles to Promote Fairness, Ethics, Accountability and Transparency (FEAT) in the Use of Artificial Intelligence and Data Analytics in Singapore's Financial Sector' (2018) <https://www.mas.gov.sg/-/media/mas/news-and-publications/monographs-and-information-papers/feat-principles-updated-7-feb-19.pdf> accessed 17 July 2024.

[1047] Available in open source at: <https://github.com/veritas-toolkit> accessed 17 July 2024.

[1048] *See* MAS, 'Veritas Document 5 – From Methodologies to Integration' (2023) <https://www.mas.gov.sg/-/media/mas/news/media-releases/veritas-document-5---from-methodologies-to-integration.pdf> accessed 17 July 2024.

Verify' toolkit introduced in May 2022 by the Infocomm Media Development Authority (IMDA) in cooperation with companies across various sectors. This other toolkit aligns with globally recognised AI governance frameworks, and it encompasses eleven principles: (i) 'transparency', (ii) 'explainability', (iii) 'repeatability/reproducibility', (iv) 'safety', (v) 'security', (vi) 'robustness', (vii) 'fairness', (viii) 'data governance', (ix) 'accountability', (x) 'human agency and oversight', and (xi) 'inclusive growth, societal and environmental well-being'.[1049] As part of Singapore's AI national strategy, in January 2020, IMDA and the Personal Data Protection Commission (PDPC) launched the second edition of the 'Model AI Governance Framework', an instrument of soft law intended to guide organisations in translating ethical principles into practical solutions for responsible AI adoption.[1050]

As another example, in March 2023, the UK government adopted a pro-innovation approach to AI regulation applicable across all sectors of its national economy. The UK approach is based on five principles: (i) 'safety, security and robustness', (ii) 'appropriate transparency and explainability', (iii) 'fairness', (iv) 'accountability and governance', and (v) 'contestability and redress'.[1051]

In Canada, the financial regulator, Office of the Superintendent of Financial Institutions (OSFI), in collaboration with industry participants and academia, published a report in April 2023 outlining four core principles for responsible AI,

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1049 *See* AI Verify Foundation, 'Summary Report: Binary Classification Model for Credit Risk ABC Company PTE LTD' (6 June 2023) <https://aiverifyfoundation.sg/downloads/AI_Verify_Sample_Report.pdf> accessed 17 July 2024.

1050 *See* IMDA and PDPC, 'Model Artificial Intelligence Governance Framework: Second Edition' (2020) <https://www.pdpc.gov.sg/-/media/Files/PDPC/PDF-Files/Resource-for-Organisation/AI/SGModelAIGovFramework2.pdf> accessed 17 July 2024.

1051 *See* UK Department for Science, Innovation & Technology, 'A Pro-Innovation Approach to AI Regulation' (March 2023) <https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1176103/a-pro-innovation-approach-to-ai-regulation-amended-web-ready.pdf> accessed 17 July 2024.

known as ‘EDGE Principles’, encompassing: (i) ‘explainability’, (ii) ‘data’, (iii) ‘governance’, and (iv) ‘ethics’.[1052]

In the US, in June 2023, the SEC proposed a new regulatory framework for the use of AI by broker-dealers and investment advisers. This framework is proposed to establish extensive governance and testing regimes as well as detailed policies and procedures for AI-powered technologies.[1053]

Furthermore, Taiwan’s Financial Supervisory Commission (FSC) launched a public consultation in August 2023 on its draft principles and policies concerning the use of AI by financial institutions. The draft outlines six key principles for AI governance: (i) ‘governance and accountability’, (ii) ‘fairness and human-centric values’, (iii) ‘privacy and customer rights’, (iv) ‘system robustness and security’, (v) ‘transparency and explainability’, and (vi) ‘sustainable development’.[1054] After the solicitation of external feedbacks, the FSC officially released a final version of the document.[1055] In addition to this set of guiding principles, the FSC is also considering the need to review and reform relevant regulations applicable to AI use in financial services.[1056]

1052 *See* OSFI, ‘Financial Industry Forum on Artificial Intelligence: A Canadian Perspective on Responsible AI’ (April 2023) <https://www.osfi-bsif.gc.ca/Eng/Docs/ai-ia.pdf> accessed 17 July 2024.

1053 *See* SEC, ‘Conflict of Interest Associated with the Use of Predictive Analytics by Broker-Dealers and Investment Advisers, SEC Proposed Rule, SEC Rel. Nos. 34-97990 and IA-6453 (26 July 2023) (release) <https://www.sec.gov/files/rules/proposed/2023/34-97990.pdf> accessed 17 July 2024.

1054 *See* FSC, ‘The FSC Seeks Public Feedback on Draft Principles and Policies Regarding the Use of AI in the Financial Industry’ (August 15, 2023) Press Release <https://www.fsc.gov.tw/en/home.jsp?id=54&parentpath=0,2&mcustomize=multimessage_view.jsp&dataserno=202308280001&dtable=News> accessed 17 July 2024.

1055 *See* FSC, ‘The FSC Publishes Core Principles and Policies for AI Applications in the Financial Industry’ (17 October 2023) Press Release <https://www.fsc.gov.tw/en/home.jsp?id=54&parentpath=0,2&mcustomize=multimessage_view.jsp&dataserno=202311070001&dtable=News> accessed 17 July 2024.

1056 Ibid.

The above examples testify to the activation of several initiatives among the world's leading jurisdictions and economies.[1057] It should be noted, however, that these initiatives only concern the establishment of principles and guidelines for AI governance in financial services. But being only instruments of soft law, their adoption by firms is voluntary. Consequently, the effectiveness of these tools in ensuring trustworthy AI adoption within the industry remains questionable.

ii. From principles to practice

While emerging regulatory frameworks, including guidance and high-level principles, provide a useful starting point for effective AI governance, translating these concepts into concrete, practical solutions present a number of challenges.[1058] At the same time, efforts to shape the current debate on AI governance and regulation have also emerged among industry participants,[1059] self-regulated organisations,[1060] as well as tech firms.[1061]

[1057] For an overview of other recent regulatory efforts by national financial regulators worldwide, see Zetzsche and others (n 624) 28-34, reporting on the cases of the European ESAs, De Nederlandsche Bank, and the Hong Kong Monetary Authority; *see also* Prenio and Yong (n 973) 5. Even at the supranational level, financial regulators have begun to issue guidance and promote principles with the goal of ensuring safe and responsible AI adoption. *See, e.g.*, IOSCO (n 129) 34-37, including several examples from various supra-national regulatory bodies.

[1058] *See, e.g.*, Bo Li and others, 'Trustworthy AI: From Principles to Practice' (2023) 55(9) ACM Computing Surveys, Article 177, 3-13 and 28 <https://doi.org/10.1145/3555803> accessed 17 July 2024.

[1059] *See, e.g.*, Kurshan, Shen, and Chen (n 1005), representing a research collaboration between staff at JP Morgan and US academia; HSBC, 'HSBC's Principles for the Ethical Use of Data and AI' (2022) <https://www.hsbc.com/-/files/hsbc/our-approach/risk-and-responsibility/pdfs/220308-hsbc-principles-for-the-ethical-use-of-data-and-ai.pdf> accessed 17 July 2024.

[1060] *See, e.g.*, FMSB, 'Emerging Themes and Challenges in Algorithmic Trading and Machine Learning' (April 2020) Spotlight Review <https://fmsb.com/wp-content/uploads/2020/04/FMSB-Spotlight-Review-%E2%80%98Emerging-themes-and-challenges-in-algorithmic-trading-and-machine-learning%E2%80%99.pdf> accessed 17 July 2024; FINRA (n 837), highlighting eight main aspects that investment firms should be concerned about when adopting AI: (i) model risk management, (ii) data governance, (iii) customer privacy, (iv) supervisory control systems, (v) cybersecurity, (vi) outsourcing and vendor management, (vii) record keeping, and (viii) workforce structure.

[1061] *See, e.g.*, Microsoft, Deutsche Bank, Linklaters, Standard Chartered and Visa, 'From Principles to Practice: Use Cases for Implementing Responsible AI in Financial Services' (2019) <https://www.microsoft.com/cms/api/am/binary/RE487kh> accessed 17 July 2024, exploring the

Various stakeholders are indeed proactively engaged in fostering the AI regulatory science. However, their strategic motivations may not always be entirely aligned.[1062] For this reason, achieving a harmonised and comprehensive approach to AI governance and regulation, one that truly aligns with societal values and benefits all, requires collaboration and engagement from all involved parties—including, at a minimum, governments, industry stakeholders, academia, and civil society organisations. Nevertheless, two main common themes are emerging.

First, adequate governance frameworks within investment firms are crucial for safe and responsible AI development and use. But to achieve this, firms should assign clear responsibility for the entire AI production line to adequately trained senior management and board members. Additionally, internal governance frameworks should be well-documented to ensure clear lines of accountability among all involved individuals. Interdisciplinary work teams can also ensure proper oversight of AI systems, whereas ethical codes of conduct and/or certification regimes for AI practitioners can serve as further guarantees to ensure the adoption of responsible AI.[1063]

Second, financial regulators recognise the criticality of model risk management frameworks for identifying, measuring, and mitigating AI risks.[1064] However, globally

implementation of responsible AI based on the Singapore MAS-developed FEAT principles aimed at promoting (i) fairness, (ii) ethics, (iii) accountability, and (iii) transparency in AI applications. *See also* Google, '2022 AI Principles: Progress Update' (2022) <https://ai.google/static/documents/ai-principles-2022-progress-update.pdf> accessed 17 July 2024; IBM, 'Everyday Ethics for Artificial Intelligence' (2022) <https://www.ibm.com/watson/assets/duo/pdf/everydayethics.pdf> accessed 17 July 2024; Microsoft, 'Microsoft Responsible AI Standard, v2: General Requirements' (June 2022) <https://blogs.microsoft.com/wp-content/uploads/prod/sites/5/2022/06/Microsoft-Responsible-AI-Standard-v2-General-Requirements-3.pdf> accessed 17 July 2024.

1062 *See, e.g.*, Nora von Ingersleben-Seip, 'Competition and Cooperation in Artificial Intelligence Standard Setting: Explaining emergent patterns' (2023) 40(5) Review of Policy Research 781 <https://onlinelibrary.wiley.com/doi/full/10.1111/ropr.12538> accessed 17 July 2024.

1063 *E.g.*, BoE and FCA III (n 241).

1064 *See* FMSB (n 1060); FINRA (n 837); IOSCO (2021); BoE and FCA IV (n 345); BoE and FCA III (n 241).

accepted best practices are not yet defined due, perhaps, to persistently divergent points of view among different stakeholders. As a result, investment firms are generally left to define the best approach according to their own use cases and specific internal capabilities and resources. In particular, there is no precise guidance on how to measure and evaluate aspects pertaining to model transparency and explainability, nor exist commonly agreed standards and benchmarks concerning outcome quality.[1065]

In sum, most financial regulators are still in the early stages of formulating AI-specific governance principles or guidance for financial firms. Yet, the unique challenges and complexities presented by AI call for a tailored and coordinated regulatory and supervisory response, one that accounts for the implications of AI systems and models on both conduct and prudential risks.[1066] Notably, there is a growing awareness that effective AI governance necessitates addressing AI risks and related techno-methodical as well as organisational issues through the lens of the entire AI lifecycle.[1067] For investment firms, this means implementing risk management practices that take a holistic engineering perspective on AI trading systems. Concurrently, there is a pressing need for establishing (global) standards that build upon existing benchmarks while accounting for specific characteristics, capabilities, and corresponding risks of different applications. Such standards would enable companies to foster trust among users and other stakeholders by ensuring their trading systems conform to widely accepted criteria that extend beyond current regulatory compliance requirements.[1068]

[1065] *Cf.* Sebastian Fritz-Morgenthal, Bernhard Hein, and Jochen Papenbrock, 'Financial Risk Management and Explainable, Trustworthy, Responsible AI' (2022) 5 Frontiers in Artificial Intelligence, Article 779799 <https://doi.org/10.3389/frai.2022.779799> accessed 17 July 2024.

[1066] *E.g.*, Prenio and Yong (n 973) 20.

[1067] *See, e.g.*, BoE and FCA IV (n 345).

[1068] *See, e.g.*, Dupont, Fliche, and Yang (n 1003) 3, 19, 22, and 46; Ostmann and Dorobantu (n 262) 30-32 and 55-61.

In this context, although EU financial regulators are showing increasing awareness of the emerging and potential risks associated with AI-powered trading systems and strategies, they have yet to signal any immediate plans to revise the existing regulatory framework. Given the risks and concerns highlighted in this dissertation, it is therefore essential to closely examine the limitations of current regulatory regimes, particularly in light of the uncertainties introduced by advanced applications leveraging ML and deep learning. Accordingly, the following section focuses on developing an innovative approach to regulating AI in algorithmic trading.

8.4 Towards Innovative Regulatory Approaches to AI Governance

In light of the foregoing discussion, the fundamental issue facing global financial regulators is not so much whether or not to regulate AI in financial trading, but rather *how* best to approach this challenging task. This dissertation contends that to effectively achieve this goal, regulation must aim to simultaneously achieve two complementary, though seemingly conflicting, objectives. On the one hand, it must be able to foster innovation and competition within the sector while also ensuring other public interests, namely market quality, integrity and stability. On the other hand, it must also uphold broader values such as safe, responsible, and ethical AI adoption. Therefore, based on a critical reflection on the limitations of the current regulatory regime, we offer below some thoughts on the essential elements that an innovative approach to AI regulation should include in order to be effective.

As mentioned above, the current regulatory paradigm, rooted in the principle of technology neutrality, is largely focused on *ex-ante* control of trading systems at market access, however regardless of the specific use of AI-powered technology. These market access rules are then complemented by *ex-post* behavioural control mechanisms. In this framework, ensuring that trading algorithms contribute to fair and orderly markets depends almost exclusively on the ability of private organisations to align the use of technology with the market conduct rules. Where this may not prove enough, competent authorities—and to some extent private organisations with some delegated responsibilities as well—have the role of policing compliance by monitoring trading activity and ultimately enforcing market conduct rules including through the use of sanctions. But the relentless progress of trading technology is becoming a moving target for ensuring effective market conduct supervision. In particular, the speed and pace at which AI research and practice evolve outpace improvements in supervisory frameworks. Therefore, more sophisticated applications based on specific ML methods are at risk of not being effectively regulated.[1069]

In principle, there are two potential solutions to this problem. First, improvements in scope and effectiveness could be made to existing supervisory frameworks. More robust supervision of market conduct, both from an institutional and technological perspective, is undoubtedly a desirable and necessary development considering the increased sophistication of ML-based trading systems and strategies. A more radical solution, instead, would involve seeking new regulatory approaches able to disentangle the complexity brought about by the increasing sophistication of algorithmic trading technology. As a more comprehensive alternative, however, a combination of the two approaches could yield even better results.[1070] Now, although greater supervisory capacity can only be welcomed, especially given the traditional technological disadvantage of financial supervisors *vis-à-vis* supervised entities, in the remainder of this chapter we focus on the merits of an innovative approach to regulating AI in algorithmic trading.[1071]

A. The rationale to regulate AI trading

Our investigation has shown that while existing regulatory frameworks may be suitable for ensuring the governance of more conventional AI applications, their effectiveness

[1069] *See* discussion in Chapter 6.3 and Chapter 7.2.

[1070] *Cf.* BoE and FCA IV (n 345).

[1071] It should be noted, however, that Chapter 7 above specifically addresses issues related to market conduct supervision.

faces a number of limitations with respect to ML-powered systems. However, before examining possible new regulatory approaches, it is essential to (i) clarify the main reasons supporting the regulation of AI in financial trading, and (ii) identify the general risks that regulators always face when attempting to regulate innovative technologies such as AI.

i. Justification for regulatory intervention

A key question concerns the effective need for additional regulation to ensure effective AI governance. In particular, two main objections could be raised. First, as an already highly regulated industry, financial trading may not necessarily benefit from additional regulation. As seen in Chapter 5, extensive regulatory requirements apply to financial institutions engaged in algorithmic trading. Since current regulatory regimes are already quite pervasive and detailed, there is a risk that additional requirements will unjustifiably burden firms without improving market functioning. Moreover, stricter rules may also negatively affect trading activity, decreasing total volumes, as practices with higher compliance costs may be reduced or even discontinued. However, considering the growing inadequacy of current regulatory frameworks in addressing the new risks associated with AI trading, this objection is difficult to reconcile.

As a second main objection, one may ask whether, lacking evidence regarding market failures caused specifically by AI trading, additional regulation is warranted. Indeed, it is a common conception among predominant legal theories that a key aim of financial regulation is to address problems arising from market failures. Thus, owing to the lack of precise quantification of the detrimental effects of AI trading—something that requires the unequivocal support of empirical evidence—some might argue that existing regulatory frameworks are sufficient to deter the occurrence of detrimental practices to market functioning. However, fully accommodating this objection also presents challenges. Specifically, the absence of precise data on the potential risks associated with ML-powered trading practices does not entirely negate the existence of such risks. Therefore, the assertion that pursuing innovative regulatory approaches for AI trading is futile remains, once again, unverified.

In sum, despite the possible objections that might be raised, there are sufficient reasons to justify the need for more regulation to ensure AI governance in financial trading. Mainly, financial regulation should not only pursue market efficiency but also aim at broader objectives. These include maintaining fair and orderly market conditions and promoting ethical and responsible conduct among market participants in the use of innovative technologies. As highlighted in this dissertation, achieving the latter goal requires a thorough understanding of the techno-methodical aspects and complexities of AI trading, due to ML. Unfortunately, however, both policymakers and financial regulators do not seem to possess adequate awareness and sufficient expertise on AI, including the various ML methods and possible methodical limitations of related applications in the area of financial trading.[1072]

ii. The limitations of one-size-fits-all regulatory solutions

Having established that the phenomenon of AI trading is worthy of attention and possibly reform, let us now examine the main risks that financial regulators face in tackling such a challenging task. These risks mainly involve choosing an appropriate

1072 In the last few years, multiple initiatives have been launched to empower policymakers and regulators with enhanced resources for better comprehending and dealing with all the complexities of AI governance and regulation. Notably, the 'Stanford HAI Congressional Boot Camp on Artificial Intelligence' programme, held 8-11 August 2022, was organised by Stanford University, California, in collaboration with leaders from Silicon Valley and pioneers from civil society organisations. The programme details are available at: <https://hai.stanford.edu/sites/default/files/2022-08/Boot%20Camp%20on%20AI%20Full%20Booklet%20.pdf> accessed 17 July 2024. In the EU, initiatives tailored for EU financial regulators and supervisors have also emerged. Since October 2022, the European University Institute has hosted a series of formative events on AI and digital technologies as part of the 'EU Supervisory Digital Finance Academy' (EU SDFA). The launch event's full programme is accessible at: <https://eusdfa.eui.eu/wp-content/uploads/2022/10/EU-SDFA-Launch-event-final-programme-1.pdf> accessed 17 July 2024. Details regarding the curriculum are available here: <https://eusdfa.eui.eu/wp-content/uploads/2022/10/EUSDFA-Curriculum.pdf> accessed 17 July 2024. For more comprehensive information about the ongoing work of the EU SDFA, including activities planned for 2023, visit: <https://eusdfa.eui.eu> accessed 17 July 2024. Another noteworthy example is the Scottish AI Alliance, a collaborative effort between the local government and the Data Lab, an AI and data-focused innovation centre. For more information, visit: <https://www.scottishai.com> accessed 17 July 2024.

regulatory approach to handle the nuances of different AI applications. This is mainly because getting the scope of regulations wrong can lead to undesirable outcomes. Any attempt to regulate AI, in fact, may inadvertently lead to either over-regulation or under-regulation. In this light, for example, the precise definition of the subject matter of any future AI-targeting legislation certainly plays a crucial role.

One prominent case in point is the temptation to regulate AI through one-size-fits-all (OSFA) solutions.[1073] There are at least two main reasons for this. First, OSFA regulatory approaches may unjustifiably punish certain low-risk AI applications over higher-risk ones, with the net result of unjustifiably hindering beneficial technological innovation.[1074] Second, as AI is a dynamic and evolutionary concept, also partly shaped by the particular efforts and interests of private organisations developing and using AI tools, any attempt to clearly define the term 'AI' may ultimately undermine regulatory effectiveness by limiting the scope of applicable law and regulation.[1075]

In Chapter 2, we have seen that a given algorithmic trading system may entail very different ML methods, components, and scope of application. Since AI applications in algorithmic trading represent a highly heterogeneous category, regulation must consider this diversity. This consideration implies that, based on the complexity introduced by different applications, any new regulation targeting AI must carefully calibrate its exact scope of application. Thus, the goal of regulators should not be to regulate AI *per se*, but rather to prescribe rules to best mitigate the risks posed by specific applications. In particular, this last observation also suggests that regulators should follow a proportionality principle.[1076] As pointed out in Chapters 3 and 4, in fact,

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[1073] *See* Jonas Schuett, 'Defining the Scope of AI Regulations' (2023) 15(1) Law, Innovation and Technology 60 <https://doi.org/10.1080/17579961.2023.2184135> accessed 17 July 2024.

[1074] *Cf.* AI Act; ESMA (n 61) 41-42 and 46.

[1075] *See* Schuett (n 1073) 7-11.

[1076] *See, e.g.*, BoE and FCA IV (n 345).

the exact nature and magnitude of the additional risks posed by ML-based trading depend on the specific methods employed, their particular combination and scope of application within a given trading system, as well as the specific techno-economic environment in which that system is called upon to operate. All these considerations thus allow us to reject the feasibility of pursuing OSFA regulatory approaches for AI applications in financial trading.

After highlighting the shortcomings of both the prevailing principle of technology neutrality and OSFA solutions, the next step is to delineate the optimal features of alternative innovative approaches to regulate AI in financial trading. This is the focus of the remainder of this chapter.

B. Grounding the case for a risk-based regulatory approach

As a fundamental element, an effective approach to regulating AI applications in financial trading must be able to differentiate various applications appropriately on the basis of the greater complexity, as well as the related causes, that they introduce into the functioning of capital markets. This consideration leads us to think that regulation should therefore be proportionate to the particular and additional risks arising from specific applications. Moreover, the analysis of these risks should duly take into account those precise risk factors present in a given AI trading system or strategy. These factors include, for instance, the exact ML methods and components employed, as well as their capability and criticality when operating in real market contexts. In short, regulation should follow a proportional and risk-based approach. In the following, we (*i*) illustrate how such an approach takes inspiration from the EU AI Act framework, and (*ii*) describe the benefits of a risk-based approach to AI regulation in the context of our analysis.

i. The EU AI Act as a model of risk-based regulation

The EU AI Act represents a prime example of a risk-based regulatory approach for AI applications. It provides a first useful conceptual and prospective legal framework to classify different AI applications by delineating their dimensions of risk (and complexity). It is worth noting, however, that the scope of the AI Act is limited to AI applications that present concrete risks to individuals' safety and fundamental rights. As such, it does not address purely economic risks (i.e. financial losses) *per se*. For this reason, its applicability to AI applications in the financial sector could be somewhat limited.[1077] In particular, whether the AI Act is intended to address the risks emerging within the financial trading domain, as outlined in this dissertation, remains ambiguous. Indeed, whereas emerging attempts to regulate AI strictly focus on the immediate risks posed by AI applications, at the same time, they risk dangerously neglecting the possible occurrence of catastrophic 'black swan' events.[1078] This notably can be the case of risks arising to global capital markets whenever, for instance, market integrity becomes compromised.[1079]

For the sake of our analysis, however, this dissertation refrains from exploring the philosophical-legal question of whether financial interests, as purely economic rights, deserve legal protection in the same way as fundamental rights.[1080] Instead, preferring a focused stance, we more simply assert the necessity for ethical and responsible considerations to form the foundation for regulating AI applications in capital markets. This perspective, thus, advocates for a broader regulatory scope

[1077] *See* footnote n. 1035 and accompanying text.

[1078] The term 'black swan' event is credited to Nassim Nicholas Taleb. It describes an unexpected and rare event with severe and often irreparable effects and that is characterised by retrospective predictability. Therefore, 'black swan' events fall outside the domain of 'normal' expectations and are often attributed to human cognitive biases and the limitations of forecasting based on historical observations. *See* Nassim N Taleb, *The Black Swan: The Impact of the Highly Improbable* (Random House 2010).

[1079] *See* Noam Kolt, 'Algorithmic Black Swans' (2023) 101 Washington University Law Review (forthcoming), <https://ssrn.com/abstract=4370566> accessed 17 July 2024.

[1080] *Cf*. Filippo Annunziata, 'Towards an EU Charter for the Protection of End Users in Financial Markets' (2022) European Banking Institute Working Paper Series 2022 – no. 128 <https://ssrn.com/abstract=4200502> accessed 17 July 2024.

beyond the traditional emphasis on market efficiency rationales.[1081] Accordingly, the risk-based regulatory approach taken in the AI Act can represent a guiding normative framework to design a more effective regulatory regime for AI applications in financial trading.

To the best of the author's knowledge, this dissertation is the first treatise that evaluates the merits of a risk-based regulatory approach, as derived from the EU AI Act, using algorithmic trading, in breadth and depth, as an explanatory use case.

ii. Risk-based regulation of AI trading

As not all AI applications show the same criticality, financial regulators can benefit from adopting a risk-oriented approach to the regulation of algorithmic trading. A risk-based approach could help regulators disentangle AI-induced complexity in capital markets, allowing them to classify different AI trading tools and applications depending on the perceived risks.[1082]

To effectively capture the various levels of risk associated with different AI applications, however, financial regulators would be required to:

(i) define the additional risks to markets due to ML that warrant closer scrutiny;

(ii) identify the main critical factors in ML-based applications that may facilitate the occurrence of these risks; and

1081 *See, e.g.*, Carsten Maple and others, 'The AI Revolution: Opportunities and Challenges for the Finance Sector' (The Alan Turing Institute 2023) <https://doi.org/10.48550/arXiv.2308.16538> accessed 17 July 2024.

1082 There is indeed an emerging consensus among different stakeholders in favour of a risk-based approach to regulating AI applications. *See, e.g.*, Trilateral Research, Gabriella Ezeani and others, 'A Survey of Artificial Intelligence Risk Assessment Methodologies - The Global State of Play and Leading Practices' (Ernst & Young LLP 2021) <https://www.trilateralresearch.com/wp-content/uploads/2022/01/A-survey-of-AI-Risk-Assessment-Methodologies-full-report.pdf> accessed 17 July 2024.

(iii) determine which of these techno-methodical properties call for special regulatory treatment.[1083]

In other words, the regulatory response should be carefully calibrated, thus proportional to the risks posed by specific ML approaches and applications. However, all this suggests that regulators should best invest in developing a more precise understanding and more robust expertise to deal with enhanced system complexity and the additional risks posed by ML and 'Deep Computational Finance'.

As with other regulatory approaches, though, implementing risk-based regulation faces challenges. At one extreme, there is the risk of over-regulation.[1084] This risk, for example, can occur whenever regulatory requirements, resulting from the definition of various risk levels for regulated activities, are disproportionate to the actual risks posed by specific AI applications. At the other extreme, instead, lack of understanding—or even inaction—by regulators can lead to the establishment of an algorithmic *wild west* business culture within the industry. Both scenarios should preferably be avoided. As an ideal, indeed, regulators should maintain a role as co-producers of markets, along with economic actors as well as publicly funded academia, in order to install a culture of a fairly regulated industry that is able to ensure financial stability and market integrity without sacrificing technological innovation. To achieve this goal, though, regulators need to become more knowledgeable about the implications of AI for capital markets trading. On the one hand, they need to properly understand the specific technological aspects of AI tools for financial trading, which, because of ML, can become the cause of additional uncertainty and market risk. On the other hand, they must also consider how these aspects are shaping new agency

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1083 *See, e.g.*, Schuett (n 1073) 12-17.

1084 *Cf., e.g.*, Bernd W Wirtz, Jan C Weyerer, and Ines Kehl, 'Governance of Artificial Intelligence: A Risk and Guideline-Based Integrative Framework' (2022) 39(4) Government Information Quarterly, Article 101685, 11-12 <https://doi.org/10.1016/j.giq.2022.101685> accessed 17 July 2024, who also assess some possible solutions to avoid risks of AI over-regulation.

problems within firms, as well as how these are altering the interactions between various market players and the functioning of the market itself.

Undoubtedly, governments worldwide have recognised the importance of risk management and have turned to risk governance and risk-based regulation to guide their policy decision-making. Drawing on insights from risk studies, they seek to create effective strategies to identify and manage potential risks. In parallel, scholars have approached the study of risk-based modes of regulation, examining their effectiveness and exploring new ideas for improving risk governance and regulation.[1085]

iii. *The benefits offered by risk-based regulation*

In essence, the main goal of risk-based regulation (and governance) is to manage potential future adverse events. This regulatory approach is based on the belief that risks can be identified, anticipated, controlled, and mitigated.[1086] At the same time, though, it also recognises the inherent impossibility of fully mitigating certain risks, some of which may even have potentially catastrophic effects.[1087] Despite its possible limitations, however, risk-based regulation can provide public authorities with objective criteria for allocating enforcement resources. This approach enables them to concentrate their limited resources and attention on the most pressing and relevant issues within a clearly delineated risk framework.[1088]

1085 *See* Jeroen van der Heijden, 'Risk as an Approach to Regulatory Governance: An Evidence Synthesis and Research Agenda' (2021) 11(3) Sage Open 1 <https://journals.sagepub.com/doi/full/10.1177/21582440211032202> accessed 17 July 2024.

1086 *E.g.*, Bridget M Hutter, 'A Risk Regulation Perspective on Regulatory Excellence' in Cary Coglianese (ed), *Achieving Regulatory Excellence* (Brooking Institution Press 2017) 102 <https://pennreg.org/regulatory-excellence/wp-content/uploads/sites/5/2023/01/hutter-ppr-bicregulatordiscussionpaper-06-2015.pdf> accessed 17 July 2024.

1087 *E.g.*, Arjen Boin, 'Preparing for Future Crises: Lessons from Research' in Bridget M Hutter (ed), *Anticipating Risk and Organizing Risk Regulation* (Cambridge University Press 2010) 248 <https://doi.org/10.1017/CBO9780511761553.012> accessed 17 July 2024.

1088 Julia Black and Robert Baldwin, 'Really Responsive Risk-Based Regulation' (2010) 32(2) Law & Policy 181 <https://doi.org/10.1111/j.1467-9930.2010.00318.x> accessed 17 July 2024.

Ideally, any new regulation targeting AI trading should build upon existing regulatory frameworks and work incrementally.[1089] This approach seeks to encourage regulated entities to put in place more robust AI governance by leveraging established risk management programmes, compliance functions, and pertinent industry practices. In this way, regulation aims to promote ethical conduct in AI adoption without imposing overly burdensome and costly requirements on market players.[1090] Hence, categorising algorithmic trading systems based on risk-related metrics offers a pragmatic avenue for technology governance, rendering regulatory requirements to be proportionate to identified risks. However, adopting a risk-based categorisation framework for AI systems (or components) also presents notable implementation hurdles: primarily, how to define the different risk categories effectively.

iv. Towards a risk-based categorisation of AI applications in finance

One main challenge in implementing risk-based regulation for algorithmic trading relates to the challenging task of various applications according to pre-determined risk levels. As a possible solution, this dissertation introduces the concept of an engineering approach to AI regulation *à la* De Silva and Alahakoon.[1091] Grounded on the concept of the AI lifecycle, such an approach is intended to assist financial regulators in making sense of all the complexity inherent in AI applications for financial trading. The basic idea is that an engineering approach to AI regulation can provide a more robust framework to discern between various applications, including the corresponding AI

[1089] *E.g.*, OECD (n 135) 51; Asia Securities Industry & Financial Markets Association (ASIFMA), 'Enabling an Efficient Regulatory Environment for AI' (June 2021) 12 <https://www.asifma.org/wp-content/uploads/2021/06/enabling-an-efficient-regulatory-environment-for-ai-report_june-2021.pdf> accessed 17 July 2024; UK Department for Science, Innovation & Technology (n 1051).

[1090] *But see* Yeoh (n 96), who argues that current regulatory frameworks already imply costly compliance for financial firms.

[1091] *See* De Silva and Alahakoon (n 243).

components, systems, or activities that are more or less risky and, as such, more or less deserving of additional regulation.

Based on an engineering approach to regulation, financial regulators should address AI components, systems, and architectures, as well as their design goals and operational criticality, based on specific use cases. Moreover, shedding light on the various stages of the AI production line, an engineering approach to AI regulation is also aimed at empowering financial regulators to play—either themselves or through delegation to an independent body—a central role in co-producing industry and market developments along with market players.[1092] To be effective, such an approach requires, at minimum, a sound technical understanding of the different AI methods, their capabilities, and associated risks depending on the specific application domain. All this, however, ultimately underscores the need for financial regulators to develop interdisciplinary knowledge at the intersection of Finance, Law, and Computer Science.

8.5 An Engineering Approach to AI Regulation in Financial Trading

By acknowledging the process of developing AI trading systems as an industry line of production, we are prompted to reflect on the necessity of making the best use of on an engineering approach to regulating the 'AI lifecycle'.[1093]

As discussed in more details below, an engineering approach to AI regulation in finance can assist us to (A) categorise AI applications according to the different risks they pose to markets, on this basis (B) design appropriate regulatory requirements to support AI governance, thus mitigating these risks, and (C) appreciating the relevance of the concept of the 'AI lifecycle' in financial regulation.

[1092] *Cf.* De Silva and Alahakoon (n 243).

[1093] *Cf.* ibid.

A. Risk-based categorisation of AI trading applications

An engineering approach to AI regulation can facilitate the categorisation of AI applications according to the specific risks they pose to capital markets. Exactly aiming at providing further clarity and effectiveness to the proposed EU regulatory framework on AI, a recent interesting proposal suggests categorising AI systems according to a three-dimensional classification scheme based on: (i) the specific algorithmic methods employed in the system (i.e. 'Methods'); (ii) the capabilities to be achieved by that system (i.e. 'Capability'); and (iii) the level of criticality that can be attributed to it (i.e. 'Criticality').[1094] Recognising the merits of this approach, we discuss below how a similar classification framework could be successfully applied to the domain of algorithmic trading.

First, in terms of 'Methods', in Chapter 2, we provided a high-level overview of how a given algorithmic trading system can integrate and even combine various ML paradigms. We also outlined the main techno-methodical specificities present in systems that make use of specific ML paradigms—such as those based on DL methods—and examined the risks associated with them in order to ensure trustworthy applications. Second, as regards 'Capability', we have shown, in Chapters 3 and 4, that any application of AI to financial trading carries its own risks depending on the specific use case. Relatedly, depending on the specific capabilities within the whole trading cycle and its socio-economic context, AI trading tools can present very different risk levels. Lastly, in matters of 'Criticality', Chapters 3 and 4 pointed out that the potential of a given AI trading system or agent to result in harm to others ultimately depends on a number of techno-economic factors (e.g., the specific use case, ML model selection, complexity mastering with regard to action/state space and hyperparameters, trading efficiency, market power, cybersecurity, etc.), as well as regulatory and supervisory

1094 Thomas Schmid and others, 'The AI Methods, Capabilities and Criticality Grid: A Three-Dimensional Classification Scheme for Artificial Intelligence Applications' (2021) 35 KI – Künstliche Intelligenz 425 <https://doi.org/10.1007/s13218-021-00736-4> accessed 17 July 2024.

safeguards. As only one possible way to start disentangling the complexity spurred by AI, the proposed regulatory framework offers the advantage of an interdisciplinary approach at the intersection of the Finance, Law, and Computer Science scientific communities.[1095]

B. Proportional regulatory requirements to AI risks

Generally, a risk-based definition of algorithmic trading, such as the one proposed above, could provide greater legal certainty for market participants without necessarily raising compliance costs.[1096] An appropriately calibrated risk-based regulation will give rise to incremental legal requirements based on the three pillars of accountability (i.e. human responsibility and liability), transparency (e.g., regarding the ML model, computational process, and system architecture and strategy), and auditability (e.g., compliance, fairness, security, safety).[1097] In other words, to higher AI risk levels, incremental legal and regulatory requirements should apply to financial institutions and their staff. Both *ex-ante* and *ex-post* regulatory tools can contribute to regulating AI trading and its behaviour.[1098]

As mentioned above, *ex-post* measures generally aim at ensuring human control under extreme circumstances and best guaranteeing transparency and explainability of AI outcomes and processes.[1099] In addition, one often debated strategy is 'keep-the-user-in-the-loop-and-control' for safe and successful human-machine collaboration in automated AI systems.[1100] Thanks to advancements in the XAI research field, soon we

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[1095] Let alone Economics, Political/Social Sciences, Psychology and Philosophy.

[1096] *But see* ESMA (n 955) 45, 48, and 53-54.

[1097] *Cf.* OECD (n 135) 56-58.

[1098] *See* footnote n. 1007.

[1099] *See* footnote n. 1011-1012 and accompanying text.

[1100] *See, e.g.*, Buckley and others (n 624).

could also be able to develop increasingly autonomous ML-based trading that allows humans to understand and interpret their inner functioning.

Differently, *ex-ante* measures aim at regulating and shaping a given AI trading system behaviour before its deployment on markets.[1101] While *ex-ante* regulation can offer a valid regulatory option, their effectiveness can be impaired by human experts' knowledge and assumption about how AI can and should behave on markets and their ability to stress-test AI with proper quality data. Indeed, based on data-driven approaches, ML-based trading requires considering specific market settings, quality of input data, strategic goals, and stress scenarios in conducting testing, approval, and release. As both empirical and synthetic data can fail to represent actual market behaviours, regulators face substantial challenges relating to the establishment of testing environments.[1102] In addition, financial regulators are in a position of information asymmetry concerning financial institutions as not always able to determine—or lack—access to all data relevant to testing AI.

As an *ex-ante* solution, however, mandating testing for AI trading systems—in order to check for their reliable and legally compliant development before their actual application on real markets—seems an inevitable regulatory policy innovation to be explored. Although regulatory regimes already include testing as a means to audit trading algorithms, the real challenge faced by financial regulators is adapting these tests to the unique and novel risks to market integrity introduced by AI-powered trading.[1103]

Overall, innovative *ex-ante* and *ex-post* regulatory solutions can contribute to disentangling the sources of enhanced system complexity introduced by AI. Since

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[1101] *See, e.g.*, Allen (n 277) 196-201; *see also* Raschner (n 86).

[1102] ibid.

[1103] *See* discussion in Chapter 3.3, Chapter 4.4.C, and Chapter 7.3.C.

applications to financial trading can involve very different ML methods, techniques and strategies, financial regulation should provide, in a well-balanced way, varying degrees of duties for both AI developers and users. In the following, we provide some preliminary thoughts on how regulators could *co-produce* greater standardisation of ML methods, components, processes, related control mechanisms and auditing procedures (including related standards, metrics, and benchmarks) to render the potentially shadow business of AI algorithmic trading as a fairy regulated industry in the interest of society. To this end, greater standardisation and proactive regulation are intended together to strengthen AI governance and, at the same time, enable algorithmic trading to continue to thrive as a safe but nevertheless innovative regulated industry.

C. Delving into the AI lifecycle

When embracing an engineering approach to the regulation of AI trading applications, the concept of the 'AI lifecycle' takes on fundamental relevance. Importantly, delving into the 'AI lifecycle' is proposed to allow financial regulators to both strengthen their knowledge and develop a further understanding of the risks associated with AI-induced system complexity. Based on a rule-based and risk-oriented regulatory approach, ML applications to financial trading could be subject to different regulatory requirements, such as testing and certification regimes.

According to a recently published study by the Bank of England, software validation[1104] for ML-powered systems presents today completely new challenges than more deterministic AI approaches to algorithmic trading.[1105] Generally, software-related risks in ML-based systems can be grouped into three main categories: (i) 'model risk', i.e. the risks that a given ML algorithm cannot work as intended (e.g., because of

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1104 In Computer Science, the term 'software validation' refers to the part of the software development lifecycle aimed at verifying that a software system meets certain specifications and technical requirements in order to achieve its intended purpose.

1105 *See* Bakkar and others (n 239).

false model selection); (ii) 'technology risk', i.e. operational failures (e.g., due to incompatibility among system components or a system error, or security issues); and (iii) 'data risk', i.e. all possible circumstances under which input data lack quality or availability.[1106] Software validation, thus, ensures that complex software systems can work properly and meet their goals by mitigating software-related risks within a given socio-technical-and-economic application domain.

As rightly observed by some recent studies, however, while being perhaps able to address the peculiarities of more deterministic systems, established software validation frameworks within the financial sector perilously neglect key governance aspects of the AI lifecycle, including feasibility assessment, documentation, model monitoring and evaluation, and model risk assessment.[1107] Under an engineering approach to regulating the 'AI lifecycle', regulators could therefore start targeting risks arising from ML-powered algorithmic trading at the level of system and software validation. Indeed, financial regulators are also recognising the need to address aspects relating to governance framework, control functions, and assurance regimes from an AI lifecycle perspective.

More generally, based on a risk assessment, AI systems or components could be subject to more or less stricter pre-approval requirements (i.e. testing and certification) and other regulatory obligations (e.g., on human control, re-validation, etc.). In assuming the availability of a reliable framework to classify different risk levels, extremely 'high-risk' AI applications (or components) could even be prohibited when society cannot afford the related risks. 'High-risk' AI systems could be subject to a licensing regime prior to implementation. For 'no-risk' or 'low-risk' AI trading tools, instead, an exemption regime could be provided.[1108] As a general rule, however,

1106 Ibid 2-4.

1107 *See, e.g.*, Haakman and others (n 242).

1108 *Cf.* Gianclaudio Malgieri and Frank Pasquale, 'Licensing High-Risk Artificial Intelligence: Toward Ex Ante Justification for a Disruptive Technology' (2024) 52 Computer Law & Security Review, Article regulators should impose stricter regulatory requirements based on the increased risks associated with AI trading tools. Employing a framework, as delineated above, to categorise AI trading systems according to the specific risks they pose due to their unique techno-methodical specificities as well as their particular use cases represents a more reliable approach than adhering strictly to the technology neutrality principle or employing OSFA solutions.[1109] Thus, this nuanced regulatory framework emerges as a more robust tool for global financial regulators and supervisors when confronting the additional complexity introduced by ML in capital markets.

Although the regulatory framework described above is only one possible regulatory solution to address the risks introduced by ML in critical domains of society like capital markets, the real challenge facing legislators/regulators is to develop sound and sufficient theoretical and technical knowledge to be aware of and address the increasing levels of complexity introduced by AI and the resulting risks to the stability and integrity of global capital markets.

8.6 Conclusion

This chapter has addressed the emerging challenges for the governance and regulation of AI applications in financial trading. In identifying emerging sources of regulatory failures, it examined possible regulatory alternatives better suited to regulating the risks associated with AI trading.

Indeed, technological innovation within the algorithmic trading domain undoubtedly gives rise to an increasing degree of system complexity, with fundamental ramifications for the organisation and functioning of global capital markets. This, in

105899 <https://doi.org/10.1016/j.clsr.2023.105899> accessed 17 July 2024, proposing stringent licensing frameworks and requirements, as a form of *ex ante* regulation, for ‘high-risk’ AI systems.

[1109] *Cf*. Claudio Novelli and others, ‘How to Evaluate the Risks of Artificial Intelligence: A Proportionality-Based, Risk Model for the AI Act’ (2023) SSRN preprint 1 <https://ssrn.com/abstract=4464783> accessed 17 July 2024.

turn, has fundamental repercussions on the ability of existing regulatory regimes to mitigate the risks arising from integrating such technologies into capital markets and, thus, achieve public-regarding goals such as market integrity. AI-induced complexity is especially apparent in the model complexity of specific ML approaches, which, while intended to assist humans in handling market uncertainty, can paradoxically represent a source of uncertainty upscaling through their opaque, black box nature.[1110] This is particularly true for those most sophisticated applications (e.g., based on DL), which can fundamentally alter agency problems inherent in algorithmic trading.[1111] Additionally, the widespread adoption and ever-greater reliance on ML-based trading tools can have significant implications for capital markets, shaping economic relationships and the degree of interconnectedness among market players.[1112]

When applying traditional regulatory approaches to the challenges brought by new financial technologies, particularly in the case of increasingly autonomous AI trading systems (e.g., based on DRL), these can often and inevitably fall short. In this context, policymakers are faced with a trilemma: finding a balance between legal simplicity, market integrity, and innovation. And it is rare—if not impossible—for them to achieve all three goals simultaneously.[1113] Market conduct regulators face the same trilemma when attempting to fight against new forms of algorithmic market abuse created by autonomous AI trading strategies and their black boxes. As a result, AI/ML research and practice risks evolving within a somewhat 'shadowy' algorithmic trading industry. But the failure of regulatory regimes to account for and adapt to the technical specificities of ML-based algorithmic trading can have serious consequences.

[1110] *Cf.* Hilbert and Darmon (n 136); *see also* Hansen and Borch (n 248).

[1111] *See* Chapter 2.4.

[1112] *See, e.g.*, footnote n. 1110.

[1113] *See* Brummer and Yadav (n 97), who argue that to alleviate the FinTech trilemma's effects, regulators should enhance their institutional arrangements to achieve greater domestic cooperation and international coordination and rely on more self-regulation by market actors.

In this chapter, we highlighted the doubtful effectiveness of (*i*) principle-based and technology-neutral only regulatory approaches, (*ii*) self-regulation by industry participants, and (*iii*) the delegation of important regulatory functions to market operators in order to promote a culture of 'good market conduct' within the AI trading industry. Hence, with all these shortcomings in mind, this chapter has advanced the proposal of an engineering-based regulatory approach that recognises and addresses the technical complexities of AI trading systems, inspired by the risk-based regulatory approach as derived from the EU AI Act. The expectation is that by doing so, innovative forms of regulation can ensure the safe and responsible development and use of AI in the financial trading industry while promoting market integrity and welfare-enhancing innovation.

9. CONCLUDING CHAPTER

Capital markets trading is a highly challenging 'game' for human participants.[1114] The intricate interplay of market forces, spurred by a mix of economic events, global politics, investor psychology, and technological advancements, creates a highly dynamic market environment where participants must deftly operate despite a complex of interrelated uncertainties to make decisions often in a split second. In addition to a dash of luck, the key to success in this complicated 'game' requires a deep understanding of market dynamics, adept risk management, and strategic acumen.[1115]

However, we must also recognise that human nature has an intriguing aspect when it comes to 'games': the desire to win can lead some individuals to contemplate cheating as a means to gain an advantage. Such acting stems from the belief that circumventing rules or employing deceptive tactics can enhance the chance of success.[1116] This psychological facet carries implications not only in recreational games but also in professional domains such as financial markets.[1117] Throughout history,

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1114 For a classic of investment literature describing the attitude and psychology of financial professionals in dealing with the challenges posed by trading in capital markets, see Adam Smith (pseudonym of George Goodman), *The Money Game* (Random House, 1968).

1115 *Cf.* discussion in Chapter 2, Introduction and 2.1.

1116 The human tendency to engage in cheating behaviour in games and other contexts has been the subject of deep interest by numerous scientific disciplines such as, for instance, Cultural Studies, Economics, Ethics, and Psychology. *See generally* Stuart P Green, *Lying, Cheating, and Stealing: A Moral Theory of White-Collar Crime* (Oxford University Press 2007) 53-75. According to in-lab experiments, there seems to be a positive correlation between individuals' propensity to cheating and competitive pressure for a given desired reward. *See* Christiane Schwieren and Doris Weichselbaumer, 'Does Competition Enhance Performance or Cheating? A Laboratory Experiment' (2010) 31(3) Journal of Economic Psychology 241 <https://doi.org/10.1016/j.joep.2009.02.005> accessed 17 July 2024. For a comprehensive exploration of the concept of cheating within the context of cultural history of digital gameplay, see Mia Consalvo, *Cheating: Gaining Advantage in Videogames* (The MIT Press 2009).

1117 For an in-depth research study on the relationship between Psychology and Finance, see Thomas Oberlechner, *The Psychology of Ethics in the Finance and Investment Industry* (Research Foundation of CFA Institute 2007).

indeed, unfair and cheating practices have continuously evolved, partly due to technological innovation, growing increasingly sophisticated.

Following advances in the field of AI, both individuals and organisations, motivated primarily by the pursuit of financial gains and possibly personal advantage, have explored ways to endow machines with capabilities beyond human capacity. These efforts, though, may sometimes come at the detriment of the public interests of market quality and integrity—even up to the point of undermining financial stability.[1118] As the adoption of AI-powered technology transforms the way market participants operate and interact, we are called upon to investigate how new possible dimensions of misconduct may emerge in the 'game' of financial trading. As two primary objectives, hence, this dissertation set out to:

a. investigate how AI trading, powered by ML, may alter the traditional mechanics of market manipulation, considered one of the most insidious and dangerous forms of cheating in capital markets; and

b. based on this assessment, evaluate the implications for financial regulation, particularly with regard to market abuse regulations and governance of algorithmic trading.

To this end, our investigation was informed by six key questions that are at least worth recapping.

(i) In what ways does AI-powered trading introduce new risks to market integrity?

[1118] *Cf.* discussion in Chapter 3.1 and 3.2.C and Chapter 4.2.

(ii) Specifically, could AI trading systems, thanks to ML, be able to facilitate market manipulation regardless specific human intent?

(iii) If so, are existing legal and regulatory frameworks able to address the new risks introduced by AI trading?

(iv) What are the limitations in the enforcement of market conduct rules in relation to ML-powered trading? And how can those be addressed?

(v) What are the implications for existing supervisory frameworks? Can AI provide an innovative tool to enhance the market surveillance capabilities of financial supervisors?

(vi) More generally, can the current regulatory approach for algorithmic trading governance accommodate the additional uncertainties introduced by ML? If not, what innovative regulatory approaches can be envisioned?

To outline the main research findings of this dissertation, this concluding chapter is organised as follows. We first summarise the conclusions derived from Part 1 and explain the research methods employed. This allows us to address the research questions *(i)* and *(ii)* above (Chapter 9.1). Subsequently, our attention turns to Part 2 by offering a comprehensive and structured recapitulation of its constituting chapters, which deal with questions *(iii)* through *(vi)* above respectively (Chapter 9.2). Next, we share a note about the research impact the dissertation aims to have on the scientific community and its broader implications (Chapter 9.3). Moreover, a reflective analysis of encountered research limitations and prospective avenues for future research is presented (Chapter 9.4). Finally, we culminate with concluding remarks that encapsulate the key takeaways from this dissertation (Chapter 9.5).

9.1 Novel Risks of Market Manipulation Introduced by AI

In Part I, we addressed how innovation in AI and ML transforms the financial trading domain, potentially posing new risks to market integrity. By examining state-of-the-art ML research in financial trading, we have unveiled the emerging field of 'Deep Computational Finance'. These advanced methods empower human experts and private organisations to develop increasingly sophisticated and capable trading systems. On the positive side, ML offers financial researchers and practitioners the opportunity to deepen their understanding of capital markets and design more accurate and profitable trading strategies. However, there is also a darker side to the story. The autonomous and opaque nature of specific ML methods introduces new and unprecedented risks.[1119] We examined some of these risks by focusing on the rapidly evolving ML paradigm of DRL, which enables the creation of trading software agents capable of exploring their operative market environment and experimenting with various trading strategies to achieve optimal results based on predefined goals.[1120]

There are at least three main reasons why our investigation focuses on DRL agents. First, the DRL field is at the centre of the ongoing scientific debate about the risks posed by autonomous artificial agents in various application domains.[1121] Second, the Computational Finance literature itself is becoming increasingly interested in researching methods for designing trading systems able to operate with increased autonomy, as evidenced by a growing number of publications.[1122] However, it is worth noting that the inherent complexity of modelling market behaviour can make it difficult for DRL agents to master their action space. This implies that DRL methods for trading can result in poor and unreliable performance, eventually leading to

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[1119] *See* discussion in Chapter 2.4.A and 2.5.

[1120] *See* discussion in Chapter 2.4.B.

[1121] *See* discussion in Chapter 3.3 and Chapter 4.4.

[1122] *See* footnote n. 1120.

financial losses for the firms that employ them.[1123] Third, and most significantly, the potentially unpredictable and uncontrollable market behaviour of DRL agents may pose a severe threat to capital markets. Their trading activity can adversely affect market functioning and efficiency, causing severe disruptions, including engaging in market manipulation regardless of specific human intent.[1124]

This dissertation has argued that AI trading has the potential to optimise both conventional and new forms of market manipulation. While there is little doubt that malicious actors may leverage AI techniques to enhance the effectiveness of their manipulative trading strategies, the risks associated with AI trading extend far beyond. Focusing on the proprietary trading industry as a case study, we demonstrated, from a conceptual point of view, the possibility of DRL trading agents becoming so 'intelligent' as to outsmart humans—including their developers, users, and all other relevant human stakeholders—and thus be able to autonomously engage in market manipulation by self-learning from their trading experiences. By conducting a state-of-the-art analysis of ML research, particularly in the field of computational finance, we discussed these risks to occur in the context of selected trading practices, including (i) 'deceptive strategies', (ii) 'aggressive strategies', (iii) 'cross-market manipulation', and (iv) 'hybrid forms of manipulation'. However, we also highlighted the main practical and technical obstacles confronting autonomous trading agents in order to successfully engage in profitable market manipulation.[1125]

But there is more. Through the bridging of three seemingly distant research fields, namely Competition Law, Computational Finance and Computational Antitrust, we also showed that competing DRL trading agents could find ways to coordinate their behaviour in specific market segments, potentially leading to unprecedented forms of

[1123] *See* discussion in Chapter 2.5.

[1124] *See* discussion in Chapter 3.3.

[1125] *See* ibid.

algorithmic collusion.[1126] In particular, we conceptually exemplified the possibility of these risks materialising in 'financial benchmark' and 'quote-driven' markets. However, we have also identified a number of practical limitations, including especially the critical role that communication between rival algorithms plays in disinhibiting algorithmic collusion in real market contexts.[1127]

Overall, these findings not only unveil the emergence of new risks of market abuse due to ongoing innovation in AI applications for financial trading, but also underscore the importance of assessing the effectiveness of existing regulatory regimes on the governance of algorithmic trading and market abuse regulation, as well as the respective supervisory frameworks and enforcement mechanisms in place. The following section presents the conclusions reached from the assessment conducted by this dissertation.

9.2 Regulatory Implications, Challenges, and Proposed Solutions

The findings in Part 1 of this dissertation underscore the critical importance of having robust regulatory and supervisory frameworks adequately tailored to the specific risks associated with AI trading. This means that financial regulation and supervision must ensure the promotion of market integrity, particularly through the prevention of market abuse, in relation to the emergence of highly sophisticated and powerful trading systems capable, thanks to ML innovation, of operating with greater autonomy.[1128] From this perspective, Part 2 of this dissertation took a closer look at the EU regulatory and supervisory frameworks for algorithmic trading governance and market abuse. More specifically, we examined their effectiveness in addressing the

1126 *See* Chapter 4.4.

1127 *See* discussion in Chapter 4.5.

1128 The EU legal and regulatory framework of market abuse and on the governance of algorithmic trading is discussed in Chapter 5.

additional risks associated with AI trading, focusing on the phenomenon of market manipulation (and collusion).

As described in detail later in this section, we conducted a comprehensive assessment of how AI adoption can perilously challenge:

A. the safe application of the EU market abuse regulation, particularly the established liability rules for market manipulation and their enforcement mechanisms (Chapter 6);

B. the effectiveness of EU market conduct supervision, particularly the strategies and systems for monitoring trading activities currently in place (Chapter 7); and

C. the adequacy of current regulatory frameworks on the governance of algorithmic trading (Chapter 8).

These three aspects are discussed individually below.

A. Shortcomings of market abuse regulations

As a first point, our investigation uncovered several shortcomings in EU market conduct regulation to ensure effective deterrence against market abuse by AI trading.[1129] Through a careful examination of existing legal prohibitions on market manipulation, we highlighted, from a conceptual standpoint, how underlying liability concepts—such as 'intent', 'causation', 'foreseeability' and 'negligence'—find increasing application difficulties in the context of AI trading misconduct. Specifically, our findings revealed that these challenges are exacerbated by certain ML applications due to their techno-methodical specificities—namely, 'automation', 'complexity',

[1129] *See* Chapter 6.

'correlation focus', 'data dependency', 'interconnectedness', 'opacity', and 'vulnerability'.[1130] But, as trading activity is increasingly conducted by sophisticated algorithms, the realisation that market conduct rules are becoming obsolete in the face of ML-based systems calls for critical reflection on the very effectiveness of enforcement regimes.

To tackle the challenges faced by the EU market conduct enforcement regime, particularly its efficacy in deterring AI-enabled market manipulation through the threat of prosecution and sanctions, this dissertation adopted a Law & Economics approach. As argued in this dissertation, Deterrence Theory provides a valuable framework to address liability issues for misconduct by combining legal analysis with economic principles such as, for instance, efficient liability allocation, risk allocation, incentive optimisation, and negative externalities.[1131]

As a first conclusion, we proposed reforming the definition of the prohibition of market manipulation. Having identified the subjective element (i.e. *mens rea*) as the main cause of ineffectiveness, we proposed moving to a strictly harm-centred definition.[1132] Focusing only on the objective element of misconduct—i.e. the observable and quantifiable effects on prices and/or the behaviour of other market participants—, a harm-centred definition of market manipulation is proposed to better address cases of market manipulation by AI trading where, due to ML, it is notoriously difficult to determine the subjective element.[1133]

Next, we analysed the effectiveness of the EU enforcement regime, particularly its institutional structure and related enforcement mechanisms, considering the

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1130 *See* discussion in Chapter 6.1 and 6.2.

1131 See discussion in Chapter 6.4.

1132 *See* discussion in Chapter 6.5.A.

1133 Ibid.

nuances of the various Member States. Drawing upon Deterrence Theory—a well-established school of thought in Law and Economics—as a normative framework, our investigation identified serious weaknesses in the ability of the current EU regime to achieve credible deterrence against AI trading misconduct. In fact, the persistence of still too fragmented and not fully harmonised enforcement regimes among Member States, which nevertheless combine a combination of administrative and criminal liability, appears to be a major obstacle to ensuring optimal deterrence. To illustrate, while sophisticated forms of market manipulation involving AI trading have a cross-market and cross-border nature, thus requiring a cohesive and coherent enforcement approach, Member States show some discrepancies in the treatment of the MAR/MAD legal prohibitions. As a result, this dissertation finds that there remains an unlevel playing field between enforcement regimes in the EU, which give rise to risks of under-enforcement and forum shopping opportunities for malicious actors.[1134] As a possible solution to fill these gaps, we researched new models for designing an effective liability and enforcement regime. Accordingly, this dissertation advocates for a multi-layered liability regime at the EU level.[1135] Our proposed framework envisages, on the one hand, both corporate and individual criminal liability, based on a recklessness standard as opposed to intent, for serious offences. On the other hand, it prescribes dealing with less severe market manipulation cases by imposing strict liability rules for administrative offences.[1136]

Taken together, a revised legal definition of market manipulation and a new EU-wide multi-level liability regime are proposed to ensure credible deterrence of AI

[1134] *See* discussion in Chapter 6.3.

[1135] However, one might question whether a unified enforcement regime within the EU is adequate to effectively deter market manipulation, given the increasing globalisation of financial trading. This is particularly relevant given that more advanced strategies could include non-EU markets as well. While recognising the need for greater coordination among financial regulators and harmonisation of regulatory frameworks globally, our investigation focused exclusively on examining the EU regulatory framework.

[1136] *See* discussion in Chapter 6.5.B.

market manipulation within and across EU capital markets. Both measures are intended to promote the objectives of market integrity, investor protection, and financial stability in the face of evolving AI trading practices, which become increasingly sophisticated and hence difficult to identify and prosecute—thus to deter.

B. Limitations of supervisory frameworks of market conduct

As a second line of inquiry, recognising the principle that robust enforcement is closely intertwined with the intensity and outcome quality of supervision, our investigation has thus focused on assessing the effectiveness of EU market conduct supervision.[1137]

Clearly, market conduct supervision is an activity conducted primarily *ex-post*, based on the observation and analysis of trading behaviour in the markets. As such, its effectiveness is limited by the ability of financial supervisors to access trading data in an accurate and timely manner and identify suspicious behaviour through inspection of these data. Moreover, the fact that financial supervisors are not directly involved in *ex-ante* regulatory tools, such as algorithmic testing, nor in ascertaining the validity of compliance assessments by regulated entities, implies that they do not play a primary role in algorithmic auditing. Against this backdrop, we therefore examined the EU framework for market conduct supervision and its ability to effectively address sophisticated forms of market manipulation made possible by the use of AI-powered technologies. Our analysis reveals several areas for improvement in current supervisory frameworks with respect to the challenges posed by sophisticated and optimised ML-based manipulation strategies, which can also transcend individual markets and jurisdictions.[1138]

To better illustrate this point, we specifically discussed the case of 'spoofing'—an advanced manipulation practice that relies on high rates of order placement and

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[1137] *See* Chapter 7.

[1138] *See* discussion in Chapter 7.1-7.2.

cancellation to deceive other market participants and that, in the context of AI trading, can easily assume a cross-asset and cross-market nature. An examination of practices such as 'spoofing' allows us to identify three main causes of supervisory failure. First, NCAs lack effective access to relevant market data, particularly order book data, without which it is practically impossible to detect certain illicit trading practices such as 'spoofing'.[1139] Second, their heavy reliance on the cooperation from trading venues, as watchdogs, in monitoring trading activity demands a significant level of institutional trust and organisational coordination.[1140] This reliance, combined with the challenge of often having limited expertise and resources to invest and research adequately in market surveillance technology, can adversely affect the quality of supervisory outcomes. Lastly, the EU supervisory framework more generally lacks adequate supervisory mechanisms and strategies to implement cross-market and cross-border supervision of trading activity.[1141]

The discussed causes of supervisory failure elicit the conclusion that existing supervisory frameworks inadequately address the novel risks of market manipulation presented by AI trading. The latter, in fact, can optimise their manipulative strategies, eluding market surveillance efforts, consequently jeopardising the integrity of the system. This seems to be the case, in particular, for those manipulation strategies that transcend markets and national borders, given the decentralised nature of EU market conduct supervision. In light of these considerations, we therefore sought policy measures to strengthen the current supervisory framework and proposed, to this end, the establishment of a SupTech ecosystem at the EU level. Specifically, in addition to the need to equip financial regulators and supervisors with high-level AI education, we emphasised the benefits related to:

1139 *See specifically* Chapter 7.2.A.ii.

1140 *See specifically* Chapter 7.2.A.i.

1141 *See specifically* Chapter 7.2.A.iii.

(i) improvements in current data reporting regimes and associated ICT infrastructures;

(ii) a more active role for ESMA in market conduct supervision; and

(iii) more proactive use of AI, particularly ML-based SupTech tools by financial supervisors.[1142]

By and large, in fact, these measures are designed to reduce the persistent gap, both in terms of manpower and expertise, between private actors and public authorities.

Next, in considering the role of ML methods as an integral component of market conduct supervision, we examined prevailing trends in the adoption of cutting-edge technologies by advanced financial regulators as supporting evidence.[1143] Particularly, our investigation involved interviews with personnel at *The Netherlands Authority for the Financial Markets* (AFM), which provides valuable insights into the potential for financial regulators to leverage advanced AI techniques.[1144] Notably, the integration of ML with ABM methods emerges as a promising approach that can significantly enhance the scientific basis and practice of market surveillance. These novel approaches may facilitate an enhanced comprehension for financial regulators regarding complex manipulative practices like 'spoofing'.[1145] By scrutinising the conduct of distinct agents and their impact on other market participants within

[1142] *See* discussion in Chapter 7.2.B and 7.3.D.

[1143] *See* Chapter 7.3.

[1144] *See* footnotes n. 815, 872, and 875 and accompanying text.

[1145] *See specifically* Chapter 7.3.A-7.3.B.

simulated market environments, these methods offer a scientific-based analysis conducive to a deeper understanding of such practices.[1146]

Thanks to these methods, the knowledge gained about market manipulation can serve multiple purposes. First, this derived knowledge may assist financial regulators in establishing more precise and objective definitions of sophisticated forms of market manipulation, such as ‘spoofing’, contributing to a clearer understanding from a scientific perspective. This refined knowledge, in turn, can support, on the one hand, law enforcement by facilitating the detection and prosecution of market manipulation. On the other hand, it can foster regulatory compliance among regulated entities by providing them with a clearer framework for understanding which behaviour is expected of them. Consequently, these insights form the basis for developing more robust regulatory instruments, including the enhancement of current testing frameworks aimed at auditing algorithmic trading systems *ex-ante*, prior to their deployment in markets.[1147]

Notwithstanding these exciting advantages, however, it is necessary to recognise the inherent challenges of integrating ML methods into supervisory practices: most notably, ensuring the robustness, fairness, and transparency of these technological applications. Upholding these principles is indeed crucial for maintaining trust and credibility towards the regulatory framework and its processes. Ethical considerations, for example concerning algorithmic bias or unintended consequences, must be adequately addressed to avert any adverse effects on market participants or the overall functioning of capital markets.[1148]

[1146] *See specifically* Chapter 7.3.C.i.

[1147] *See specifically* Chapter 7.3.C.ii.

[1148] *See* discussion in Chapter 7.3.D.

Overall, this dissertation offers further evidence that advancements in SupTech present an opportunity to overcome the traditional technological limitations faced by regulatory authorities responsible for safeguarding market integrity.

C. The governance of AI trading

Based on emerging shortcomings in the enforcement and supervision of market conduct rules, we then examined current algorithmic trading governance frameworks in their ability to ensure safe and responsible AI adoption.[1149]

Recognising the disruptive effect of rapid advances in ML research and practice in financial trading, we identified the major limitations of the current governance regime, which is built upon the principle of technology neutrality.[1150] Under this principle, in fact, regulatory requirements for the governance of algorithmic trading apply indiscriminately to all MiFID II-regulated algorithmic trading systems, thus making no distinction between different AI applications, particularly between the use of specific ML methods. Therefore, current regulatory regimes are bound to fail in effectively capturing the specific risks associated with certain ML methods and applications. In particular, they do not seem entirely adequate to ensure effective governance of the most advanced AI trading applications.[1151]

Moreover, since different AI applications present different risks, OSFA regulatory approaches become inadequate to address the particular risks posed by specific systems.[1152] At the same time, the search for innovative modes of governance through regulation underscores the crucial need for regulatory decision makers to be equipped with adequate knowledge about AI/ML basics including the limitations and

[1149] *See* Chapter 8.

[1150] See Chapter 8.1.

[1151] Ibid.

[1152] *See specifically* Chapter 8.4.A.ii.

risks. As argued in this dissertation, this knowledge must also include an adequate understanding of the AI lifecycle concept, including the socio-technical aspects of AI applications, such as the various—partially conflicting—roles played by different AI stakeholders.[1153]

In the quest for appropriate regulatory alternatives for effective AI trading governance, we therefore examined some of the most significant developments within the policy debate on the issue. Our analysis focused on emerging legal theories within the academic literature as well as trends in AI law and policy worldwide.[1154] Hence, drawing inspiration from the EU AI Act, this dissertation follows the concept of a risk-based approach applied to the domain of AI trading regulation.[1155] To this end, one possible solution is to classify AI applications in finance in general based on risk levels, according to:

(i) the specific ML methods involved in a given system (i.e. 'Methods');

(ii) the operational capabilities of this system in the real world (i.e. 'Capability'); and

(iii) the associated risks to capital markets (i.e. 'Criticality').

It is expected that this methodological approach could allow for a more precise legal definition of algorithmic trading systems (or components) based on distinct characteristics, particularly in terms of the risks they pose to the market.[1156]

1153 *See* discussion in Chapter 8.4.

1154 *See* discussion in Chapter 8.2 and 8.3.

1155 *See* Chapter 8.4.B. It is noteworthy that this dissertation, building upon the author's prior publications, represents the very first scholarly contribution to propose and discuss a risk-based regulatory approach for algorithmic trading as derived from the EU AI Act.

1156 *See* Chapter 8.5.A.

Moreover, grounded in the concept of the AI lifecycle, the proposed approach aims to provide a safer regulatory framework to deal with the increasing complexity introduced by AI trading in capital markets. Pertinently, following an engineering approach to AI regulation allows to design proportional requirements commensurate with ascending risk levels, covering both technical and organisational aspects.[1157] Embracing an engineering approach to AI regulation offers an avenue for financial regulators to effectively monitor technological advancements within the industry. It also enables them to offer more comprehensive regulatory guidance for the governance of AI trading technology. Additionally, this approach positions regulators as co-producers of industry developments and standards. For instance, with enhanced AI proficiency, regulators can facilitate the establishment of technical benchmarks and standards that can be employed to evaluate and compare the performance of algorithmic trading systems. An engineering approach to AI regulation is therefore proposed to ensure alignment with the overarching goal of fostering 'good' AI governance.[1158] In concluding our investigation, however, we also emphasised the importance of multi-stakeholder collaboration between regulators and industry participants, including involving publicly funded research and academia, as well as the civil society, to ensure that regulatory objectives are aligned with the public good, at least in democratic societies.[1159]

Overall, the institutional framework for AI governance, as outlined by this dissertation, is intended to promote safe and responsible innovation in the interests of the economy and society at par.

[1157] *See* Chapter 8.5.B.

[1158] *See* Chapter 8.5.D.

[1159] Ibid.

9.3 Research Impact

The investigation conducted by this dissertation provides valuable insights that have both theoretical and practical implications. On a theoretical level, this dissertation stands as a pioneering exploration, in depth and breadth, of specific ML applications—notably focusing on DRL-based agents—within the domain of capital markets trading. Our examination deep dives into ML implications for financial regulation, presenting an extensive and multifaceted analysis that serve as groundwork for future research in this area. From a conceptual perspective, this dissertation has illuminated the heightened risks to market integrity posed by ML-powered trading, with a specific focus on market manipulation. It therefore contributes to deepen our understanding of the intricate interplay between AI, market manipulation and financial regulation. More generally, it contributes to the growing scholarly literature addressing the legal and regulatory challenges arising from the adoption of AI-powered technology in the economy and society.

At a more practical level, this dissertation offers a valuable resource for private organisations integrating ML into their financial trading business, potentially equipping them with a deeper understanding of the economic, legal, and ethical risks associated with the adoption of innovative technologies. In addition, this dissertation aspires to contribute to the empowerment of non-market actors in academia, politics, and civil society. Generating valuable insights for policymakers and financial regulators can guide them in prioritising and implementing initiatives in order to acquire appropriate expertise on AI-powered technology and its associated risks. Furthermore, given the rapidly evolving landscape of AI, it contributes to the ongoing discourse on AI governance and regulation in finance, providing stimulatory concepts on enhancing existing regulatory frameworks and practices, particularly with respect to its sub-field of ML methods.

9.4 Limitations and Future Research Directions

This section aims to acknowledge the limitations encountered throughout the research process, both in terms of (A) research methods, (B) scope, and (C) resources.

A. Methodical limitations

On the methodical side, the evidence gathered on the new risks of market manipulation introduced by the integration of ML into financial trading is partly selective and incomplete. This is mainly due to the proprietary nature of the information needed to investigate the phenomenon. Although this dissertation is consistently grounded in insights from the theoretical, empirical, and experimental scientific literature, the opportunity to access proprietary information from private organisations will constitute a valuable asset for future research.

In addition, further empirical research is desirable in order to assess the actual risks of market manipulation by autonomous AI agents in real market settings. Such research could benefit from a variety of methods and tools, including, for example, sandboxing, standardized benchmarking, publicly available training datasets, etc. Particularly, investigating specific factors and market conditions conducive to AI-enabled market manipulation (and collusion) remains an under-explored avenue for research. The existing experimental research, in fact, often grapples with limitations due to simulations rooted in overly simplistic assumptions, thus constraining its generalisation capacity. While there is a burgeoning literature in this nascent domain,[1160] continued research efforts are essential to advance the field beyond its initial stages.

[1160] *See, e.g.*, Barr and others (n 344); Shearer, Rauterberg, and Wellman (n 344); Cartea and others (n 345); Cartea and others (n 377); Cartea and others (n 447); Cartea and others (n 462); Dou, Goldstein, and Ji (n 470); Cartea, Chang, and Penalva (n 501); Cont and Xiong (n 502); Cartea and others (n 502).

Another methodical limitation stems from certain research assumptions. The investigation of effective governance models for mitigating risks associated with AI trading rested on the premise that sole market self-regulation may insufficiently address these challenges. Consequently, we have postulated that democratically elected public authorities should play a primary role in steering AI governance to safeguard public interests through regulation. It is however necessary to point out that even public regulation can be biased or ineffective. This is especially the case with highly technical and innovative matters such as ensuring safe and responsible AI adoption in finance. Nevertheless, our hypothesis underscores the first-order role of EU public authorities, with substantial expert knowledge level, in shaping AI governance.

Parallel to this, we assumed the superiority of the risk-based approach of the EU AI Act, as resulting at the time of writing, a useful conceptual and normative model to replicate in the context of our investigation. However, future research ought to explore alternative governance and regulatory models—including market-based solutions, self-regulation, meta-regulation, co-regulation, or hybrid approaches—to evaluate their contribution to effective AI governance in the financial sector. In considering the rapidly changing global landscape of AI law and policy, there is an opportunity not only for comparative analysis of various emerging national approaches, but also of international treaties and other policy developments.

B. Research scope limitations

The discussion about methodical limitations opens the track for addressing the main limitations of the research scope. As a first remark, our in-depth examination of ML methods applied to financial trading, particularly their potential for market manipulation and collusion, has been centred on a specific ML paradigm—DRL-based applications. This focus aligns with the current trajectory of cutting-edge scholarship in Computational Economics and Computational Finance, which endeavours to enhance our understanding of both technical and practical capabilities and limitations of 'autonomous artificial agents'. Nonetheless, a valuable avenue for future investigation involves investigating whether other emerging ML paradigms pose analogous uncertainties and threats to capital markets.

In considering the implications of AI trading to market integrity, moreover, this dissertation has exclusively dealt with scenarios involving misconduct by autonomous DRL-based trading agents, as a prime use case, operating without direct or relevant human involvement. Given that contemporary algorithmic trading systems and strategies typically require a meaningful level of human participation, such as in 'human-in-the-loop' settings, future research should shed light on various human-machine interactive frameworks. For instance, an exploration of more recent ML paradigms like RLHF and RLHI methods and their implication for market conduct and financial regulation is warranted.

On a different note, our examination primarily centred on evaluating the effectiveness of the EU regulatory framework governing algorithmic trading and market manipulation. The narrow focus of our analysis on the EU case prompts inquiries into the broader validity of this dissertation claims across other jurisdictions. Future endeavours should encompass comparative analysis across jurisdictions to identify commonalities, disparities, etc., and ultimately assess the efficacy of various regulatory approaches.

Moreover, in researching the optimal regulatory approach for AI governance in finance, this dissertation only superficially mentioned the possible economic impacts on the industry. Further research is therefore needed to assess the cost-benefit associated with various modes of governance and regulation, shedding light on the possible implications on market access, competition, and market efficiency as a result of heightened compliance costs due to additional regulatory requirements. While advocating for financial regulation that prioritises not just market efficiency but also responsible, ethical, and fair market conduct, further research is essential to appraise the cost-benefit balance. Such an assessment should include a thorough evaluation of the implications for market quality that may arise from specific regulatory approaches and the resulting requirements imposed on AI systems.

C. Resource constraints

For the sake of completeness, one last note on resource limitations is necessary. The exploration of this dissertation's subject encountered some limitations. These limitations are partly due to all the complexity inherent to AI/ML research and its application to the algorithmic trading domain. These fields are indeed characterised by rapid evolution and require interdisciplinary expertise to master. Resource constraints, such as available time and research facilities, were a prominent challenge throughout the research project. Despite these constraints, however, every effort was made to ensure a comprehensive and insightful exploration through the available research means and capacity. Thus, we can confidently conclude that, within the given parameters, this dissertation contributes meaningfully to the scholarship.

9.5 Concluding Remarks

In concluding this dissertation, it is worth recalling its original purpose: to shed light on the impact of ML-powered trading on the fair and orderly functioning of capital markets and its implications for financial regulation. Through an interdisciplinary examination of state-of-the-art literature, empirical evidence, and legal and regulatory frameworks, this dissertation stands as the very first monograph in legal scholarship that offers an in-depth exploration of three closely intertwined research areas:

1. The application of ML in financial trading, with a particular focus on DRL-based agents;
2. The additional challenges these trading technologies pose to market integrity; and

3. The resulting implications for financial regulation and technology governance within the domain of algorithmic trading.

Our investigation sought to grasp the transformative potential of ML in financial markets and to identify appropriate measures to address the legal, regulatory, ethical, and societal challenges that may arise. A holistic understanding of the legal and technological dimensions underpinning this phenomenon is essential to shaping the future of AI governance in (Deep) Computational Finance applications. Effective AI governance must promote the objectives of market integrity, fairness, effective regulation, including risk mitigation. Reflecting on Stephen Hawking's cautionary note, cited in the introductory chapter of this dissertation, analogous threats are immanent in the domain of finance: the growing risks of delegating agency to AI systems and their algorithms, with potential consequences that, should things go awry, could transcend human comprehension and control. In this context, thus, ensuring human accountability and liability for the actions of AI systems, particularly for harm inflicted on the economy and, by extension, society, remain a critical concern and a top priority for policymakers and regulators. Indeed, the pursuit of AI governance and market integrity in finance highlights the complex and nuanced interplay between technological innovation, capital markets, and societal welfare.

Amid the rapid evolution of financial technology and innovation, our common quest for a prosperous and ethical society demands a financial system grounded in publicly accountability—one that harmonise diverse and often conflicting human ambitions, motivations, and preferences while ensuring robust public oversight over private power and markets.[1161] Faced with all the complexity introduced by AI and the behind-the-scenes struggle among private powers seeking to shape the future role of AI in society, it is therefore imperative to ensure a central role for public policy and

[1161] *Cf*. Nick Bernards, 'Can Technology Democratize Finance?' (2023) 37(1) Ethics and International Affairs 81, 91-94 <https://doi.org/10.1017/S0892679423000096> accessed 17 July 2024.

regulation. Only a well-structured and normative regulatory framework may provide the appropriate foundation to balance competing private interests, mitigate harmful conflicts, and, above all, prioritise and safeguard the public interest.[1162] Just as finance transforms innovative ideas into tangible inventions and practical realities, effective AI regulation and governance—rooted in fundamental principles such as transparency, fairness, and accountability—serve as the cornerstone of a financial system that not only fosters technological progress but also uphold societal values, advance shred goals, and promote sustainability in the digital era.

1162 *Cf., e.g.*, Saule T Omarova, 'Technology v Technocracy: Fintech as a Regulatory Challenge' (2020) 6(1) Journal of Financial Regulation 75 <https://doi.org/10.1093/jfr/fjaa004> accessed 17 July 2024.

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ANNEX I: PUBLICATIONS LIST

This dissertation, presented in the form of a monograph, represent the culmination of extensive research conducted by the author. It draws upon a collection of prior works, including two co-authored papers with Professor Wolf-Georg Ringe and Professor H. Siegfried Stiehl, as well as two single-authored papers. These four foundational papers have previously undergone rigorous peer review and have been published in international journals and edited books. In this monograph, the author adapts, integrates, and extends the content of these foundational works, offering a comprehensive and cohesive examination of the subject matter. The following list provides details of these publications:

- Azzutti A, WG Ringe and HS Stiehl, 'Machine Learning, Market Manipulation and Collusion on Capital Markets: Why the 'Black Box' Matters (2021) 34 University of Pennsylvania Journal of International Law 79.

- Azzutti A, 'AI Trading and the Limits of the EU Law Enforcement Regime in Deterring Market Manipulation' (2022) 45 Computer Law & Security Review, Article 105690.

- Azzutti A, 'The Algorithmic Future of EU Market Conduct Supervision: A Preliminary Check' in L Böffel and J Schürger (eds), *Digitalisation, Sustainability and the Banking and Capital Union* (Palgrave Macmillan 2023) 53-98.

- Azzutti A, WG Ringe and HS Stiehl, 'Regulating AI Trading from an AI Lifecycle Perspective' in N Remolina and A Gurrea-Martinez (eds), *Artificial Intelligence in Finance: Challenges, Opportunities and Regulatory Developments* (Edward Elgar Publishing 2023) 198-242.