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Mechanisms of Context Effects in Multi-alternative Decisions

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1 | Introduction

Summary

Decision-making is one of the most fundamental cognitive processes, in which the evaluation of multiple alternatives leads to an ultimate choice. The evaluation process involves assigning a value to each alternative based on their objective attributes and the subjective preferences of the decision-maker. This process can result in either a rational or an irrational choice. According to rational choice theory, rational choices are those in which the best alternative is always chosen independent of any other contextual factors. This can happen when the value of each alternative is evaluated in isolation, but not relative to the other contextual factors, such as the properties of other competing alternatives. However, real-world behavior often diverges from this theory; it has been shown that the decision-making process can systematically deviate from the normal path, resulting in an unexpected (i.e., irrational) choices. Contextual factors, such as the number of alternatives, the arrangement of the attributes, and the information flow over time play an important role in these deviations from the norm. Understanding how different aspects of the contexts, including the presence of multiple alternatives influence the choice behavior is the central focus of this dissertation. In this chapter, I will outline the basic definitions needed to better understand the purpose and results of my dissertation.

Contextual effects on decision-making

Have you ever thought about how many decisions you make every day? (You can simply ask ChatGPT or scan the QR code in Figure S1 in Extended Data). Making decisions is an inseparable part of our lives, from simple choices like choosing between a doughnut and a Franzbrötchen for our evening snack, to complicated ones like having a baby. Imagine that you usually buy a sweet snack with your evening coffee, such as a doughnut or a Franzbrötchen. You usually prefer the Franzbrötchen to the doughnut when they are the only available options in the store (Figure 1B, 2 bars on the left). But magically, your preference might change on days when the seller offers the special day's snack, for example, the cinnamon roll (Figure 1B, 2 bars on the right). After a while, you might wonder, "Why did I buy a doughnut most of the time this week when a third option was offered?" or "What caused me to make that choice?" The simple answer is the context; the context of your decisions (here the number of options in your choice set) was different on the days when you preferred the doughnut to the Franzbrötchen.

Figure 1. A toy example of every day choices. (A) The choice between the most preferred snacks (on the left) might change if the salesperson offers a third snack. **(B)** A schematic of the change of preference when a third option is added.

Contextual aspects, such as the number of alternatives or the attributes, often derail the decision process from the normative expectations (Huber et al., 1982a; Simonson, 1989; Tversky, 1972; Tversky & Kahneman, 1981). Empirical evidence has shown several forms of context effects on multi-alternative decisions, when the preference between two alternatives is altered by the addition of a third (often inferior) alternative (Cao & Tsetsos, 2023; Cataldo & Cohen, 2021, 2021; Chau et al., 2020; Dumbalska et al., 2020; Evangelidis et al., 2018, 2024; Huber et al., 1982a; Y. Liu & Trueblood, 2023; Louie et al., 2013; Louie & De Martino, 2014; Noguchi & Stewart, 2014;

Parrish et al., 2015; Simonson, 1989; Soltani et al., 2012; Spektor et al., 2021; J. S. Trueblood et al., 2013; Tsetsos, Chater, et al., 2012; Tversky, 1972; Webb et al., 2021). Context effects were first observed in complex multi-attribute choices, a class of phenomena known as ***decoy effects*** (Evangelidis et al., 2024; Huber et al., 1982a; Simonson, 1989; Spektor et al., 2021; Tversky, 1972). More recently, however, a novel context effect has been reported in single-attribute decisions, known as the ***distractor effect*** (Chau et al., 2020; Itthipuripat et al., 2015; Louie et al., 2013). Additionally, although context effects have typically been studied in the domain of ***value-based*** decisions (i.e., hypothetical consumer choices or choices based on maximizing total reward), it has subsequently been shown that context effects are also present in ***perceptual*** decisions (Choplin & Hummel, 2005; Parrish et al., 2015; J. S. Trueblood et al., 2013). This suggests that context effects might be driven by domain-general cognitive principles.

Perceptual decision-making

We make many perceptual decisions every day: Which pen is red? Is the traffic light green allowing us to cross the street? Is it dark enough outside to turn on the light? How hot is my coffee? These decisions are less complex and can be made quickly, with less effort and deliberation. Thus, the study of perceptual decisions has been a primary focus of decision neuroscience over the past decades, providing insights into various aspects of the behavioral, computational, and neural mechanisms of decision-making (Gold & Shadlen, 2007; Kiani et al., 2006; Shadlen & Newsome, 2001a). Perceptual decision-making is the process by which individuals make choices based on integrating sensory evidence over time until a decision boundary is reached. This process typically involves three distinct stages: 1- Sensory encoding, where sensory input is processed and passed on to the next stage; 2- Information integration, where encoded sensory evidence is gradually integrated over time; and 3- Action selection, where integrated information triggers an action plan when accumulated evidence reaches a predefined decision threshold (Shadlen & Kiani, 2013; Shadlen & Newsome, 2001a). Accordingly, a class of sequential sampling models that assume this feedforward mechanism based on evidence integration has been proposed to explain the decision-making process. This can account for simple binary decisions to multiple alternative decisions (Gold & Shadlen, 2007; Kiani et al., 2006; Ratcliff & Smith, 2004; Smith & Ratcliff, 2004; Tsetsos, Gao, et al., 2012; Usher & McClelland, 2001).

Visual perceptual tasks, which are concerned with how observers discriminate and detect visual stimuli (e.g., brightness, shapes), are a group of tasks extensively used to shed light on the various aspects of decision-making. Figure 2A illustrates an example of a visual discrimination task that has been used to investigate the mechanisms of multi-alternative decision-making using nonstationary information. Here, four patches were presented on the screen (Tsetsos et al., 2011). The brightness of each patch varied and was updated every 13.3 ms. Human participants were instructed to choose the overall brightest patch at the end of stimulus presentation. Figure 2B gives an example of a size discrimination task used to study context effects in primates (Parrish et al., 2015). Three rectangles of different sizes appeared on the screen and the monkey was rewarded for choosing the one that had the largest area.

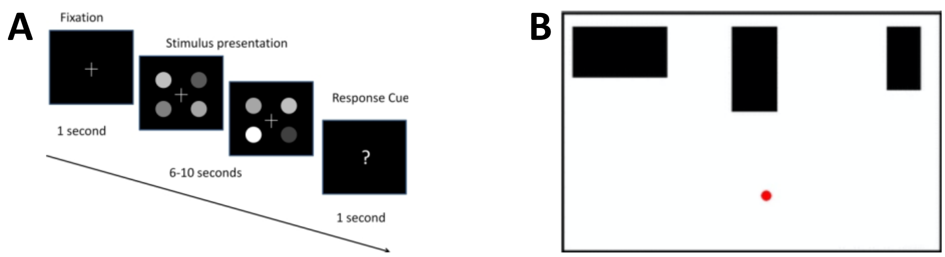

Figure 2. Examples of perceptual task. (A) The brightness discrimination task, adapted from (Tsetsos et al., 2011). **(B)** A size discrimination task, adapted from (Parrish et al., 2015).

Value-based decision-making

Value-based choices are another set of decisions we face every day. Is it worth buying new or used furniture? Is it better to invest in crypto or stocks? Is it worth eating less sugary foods? Which flight is better? In contrast to perceptual decisions, value-based decisions are based on complex information (e.g., more than one attributes), require more effort, and longer deliberation, and, importantly their outcome can have a larger impact on our lives. So, the exploration of value-based decision-making has attracted increasing interest in a variety of fields, including neuroscience, psychology, economics, computer science, and statistics. Value-based decision-making involves evaluating trade-offs, costs, benefits, and risks to maximize the desired objective. It has been proposed that a multilevel computational framework can account for this process: 1- Subjective value representation, where the integration of various external features of alternatives and internal preferences forms a subjective value. 2- Action selection, where an alternative that satisfies the desired goal (the one with the highest subjective value) is selected. 3- Outcome evaluation, which is used to learn from experience to improve the quality of future decisions and maximize the overall expected outcome (Levy & Glimcher, 2012; M. L. Platt & Plassmann, 2014; Rangel et al., 2008).

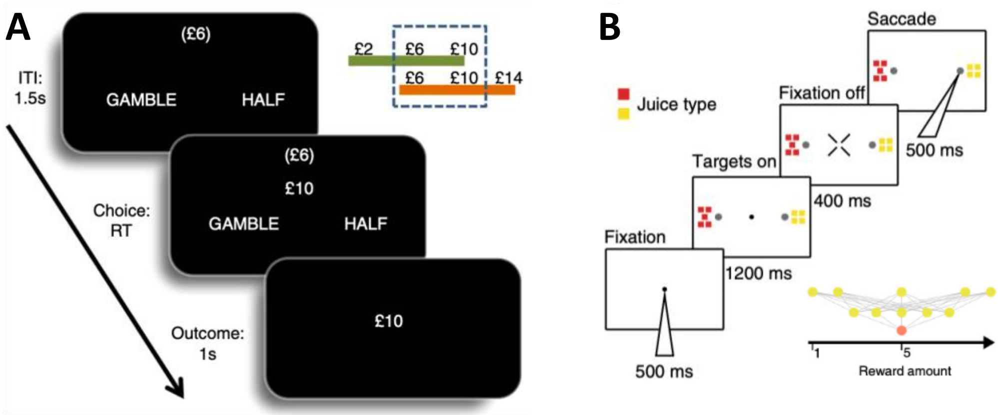

Figure 3. Examples of value-based task. (A) A gambling task to study the influence of the reward range as a contextual factor on the choice behavior, adapted from (Rigoli et al., 2016). **(B)** A value-based task to study adaptive choice behavior in Monkey, adapted from (Zimmermann et al., 2018).

Figure 3 shows two examples of value-based decision tasks. In Figure 3A, human participants were presented with a monetary reward on the screen (here £10). They were instructed to choose between a half option, which ensured that they would receive half of the reward, or a gamble, which had a 50% chance of resulting in either the full amount of the reward or zero. This task was designed to study the influence of the reward range (green and orange in Figure 3A, referred to as two distinct contexts) on choice behavior (Rigoli et al., 2016). Figure 3B is another example of a value-based task used to study adaptive choice behavior in monkeys. They trained monkeys to choose between two options with different reward amounts and juice types. The reward amount and juice type of one option (here red) remained constant while the reward amount of the other option varied (Zimmermann et al., 2018). A common feature of this value-based task is that participants would gain a reward (e.g., a monetary payment) based on their task performance eventually.

Distractor effects

Independence of irrelevant alternatives (IIA) is an axiom of decision theory that is considered a necessary condition for rational behavior. This axiom states that the decision between two high-quality alternatives (i.e., best and second-best) should not depend on either the quality or the availability of a third inferior alternative (Luce, 1959; Rieskamp et al., 2006). However, the empirical evidence violates this principle. It has been shown that the choice between a high-value (HV) and a lower-value (LV) alternative can be influenced by the value of a third distractor alternative (DV) whose value is lower than both the HV and the LV. This phenomenon is known as the distractor effect (Chang et al., 2019; Chau et al., 2014, 2020; Itthipuripat et al., 2015, 2015; Louie et al., 2013; Webb et al., 2020). The distractor alternative can influence the relative choice share of HV over LV in either a negative or a positive way. In the *negative distractor* effect, a higher DV alternative reduces the tendency to choose HV over LV, as depicted in the two left bars in Figure 4 (Itthipuripat et al., 2015; Kohl et al., 2023; Louie et al., 2013). In contrast, in the *positive distractor* effect, the tendency to choose HV over LV increases as the value of the DV increases, as depicted in Figure 4 two middle bars (Chang et al., 2019; Chau et al., 2014, 2020). The absence of the distractor effect, as shown in Figure 4 two right bars, can also occur and is consistent with the IIA (Gluth et al., 2020; Itthipuripat et al., 2019).

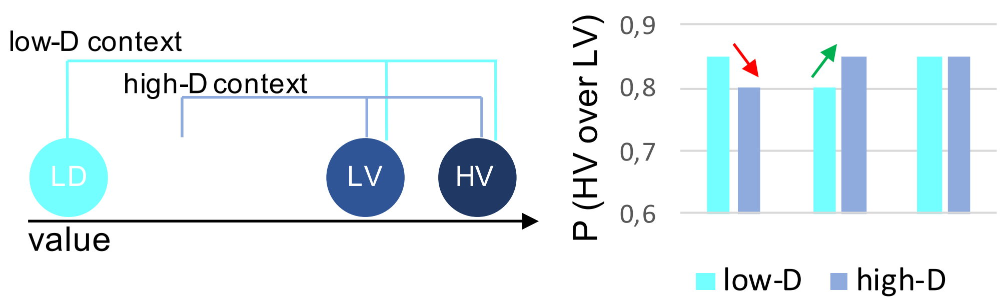

Figure 4. Schematic of distractor effects on choice. The choice between two high-value alternatives (HV and LV) can be influenced either positively or negatively by the value of the third distractor alternative in the choice set. The first two bars on the left and the two middle bars depict a positive or negative influence, respectively. The last two bars on the right depict a null distractor effect on choice.

Decoy effects

Decoy effects are another form of context effects that violate the IIA mentioned above. These effects have been observed in more complex decisions involving multiple attributes (Evangelidis et al., 2024; Huber et al., 1982a; Huber & Puto, 1983; Simonson, 1989; Spektor et al., 2021; Tsetsos et al., 2010; Tsetsos, Chater, et al., 2012; Tversky, 1972). For example, a preference for A (e.g., an expensive organic product) over B (e.g., an inexpensive nonorganic product) may shift irrationally when a third inferior alternative D (e.g., an overpriced nonorganic product) is added to the choice set.

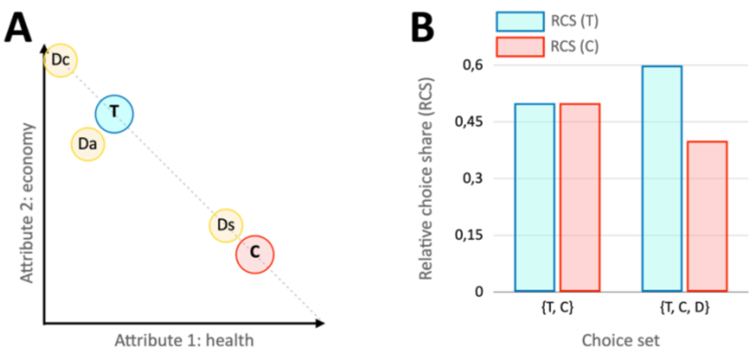

Figure 5. Schematic of decoy effects. **(A)** Illustration of the choice sets that lead to the attraction, compromise, and similarity effects. T and C indicate two equally preferred alternatives, and Da, Dc, and Ds are the decoy alternatives leading to attraction, compromise, and similarity effects respectively. T refers to "target" and C is the "competitor". D is known as "decoy" the alternative that is specifically arranged within a choice set in order to increase the choice share of the target alternative. **(B)** Relative choice share of T and C illustrating a bias in favour of the target. Left bars show that T and C are equally preferred when they are alone in the choice set and right bars illustrates how adding the decoy alternative influences the relative choice share of T and C.

IIA posits that the relative choice share between two equally valued alternatives should be independent of the presence of a third, inferior, "*decoy*" alternative (Luce, 1959, 1977; Tversky, 1969). However, empirical findings have shown that the choice share between two equally preferred alternatives, "*target*" and "*competitor*," changes in the presence of the decoy (Dumbalska et al., 2020; Evangelidis et al., 2018; Hasan & Trueblood, 2024; Y. Liu & Trueblood, 2023; Spektor et al., 2021; J. S. Trueblood et al., 2013; J. S. Trueblood & Pettibone, 2017; Tsetsos et al., 2010; Tsetsos, Chater, et al., 2012). Target is the alternative within a choice set whose choice share is expected to increase when the decoy alternative is introduced, while competitor is the alternative whose choice share is expected to decrease in the presence of the decoy. Different spatial arrangements of the decoy alternative relative to the target and competitor in attribute space result in different decoy effects (Figure 5A). Similarity (Tversky, 1972), attraction (Huber et al., 1982a), and compromise (Simonson, 1989) effects have been reported as the three main classical decoy effects.

Efficient neural coding can lead to context-dependence

Various forms of contextual effects observed in choice behavior suggest that the neurobiological decision-making process relies on relative valuation rather than absolute coding. Context dependence is a common feature of neural coding, particularly in sensory processing and attention (Carandini & Heeger, 1994, 2011). Higher surround suppression is an example of relative neural coding in the primary visual cortex. Figure 6 shows that the neural response to an identical disk contrast decreases with increasing surround contrast. Unlike behavioral metrics, neural activity operates within defined minimum and maximum thresholds. Thus, these neurobiological constraints may contribute to numerous cases of context-related effects on valuation and decision behavior.

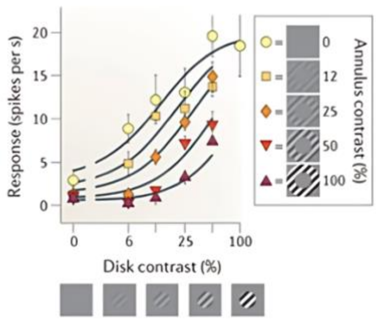

Figure 6. Surround suppression in primary visual cortex. The response to a central disk, presented in x-axis, was suppressed by increasing the surrounding contrast, presented on the right, adapted from (Carandini & Heeger, 2011).

Efficient decision-making in organisms relies on predicting the consequences of actions and selecting the most favorable choices based on their associated rewards or costs. Economic theory emphasizes the role of subjective values over objective values in decision-making. Neural evidence has also shown that brain activity associated with rewards is more closely related to subjective value than to objective measures (Lim et al., 2011; Louie & Glimcher, 2012; M. Platt & Padoa-Schioppa, 2009). Based on the neural and behavioral evidence, decision-making processes can be influenced by the stochastic and relative value representation process, which is shaped by a contextual factor (Elliott et al., 2008; Louie et al., 2011; Soltani & Koechlin, 2022). The contextual factor can be either immediate or temporal. In the following sections, I have briefly reviewed how immediate and temporal contexts influence brain areas involved in the valuation and decision-making process.

Immediate context-dependence

Immediate context-dependence in decision-making refers to the influence of information, which is available simultaneously at the choice moment, during the decision-making process. This means that neurons represent the information specific to an alternative relative to the surrounding context at the same time. The arrangement, the number, and the total value of the presented alternatives are examples of immediate-context modulations that impact the valuation and choice behavior.

Recent neurophysiological studies show that immediate context modulation of value encoding plays an important role in subjective value representation and emerging the subsequent choice context effects. In 2011, Louie et al. showed that neurons in the parietal areas of monkeys encode target values relative to total presented values by adjusting firing rates based on the spatial context defined by all available choice alternatives (Louie et al., 2011). They recorded the responses of LIP neurons during two different forced-choice tasks. Figure 7 shows one of these tasks in which the target value (V_in, presented in the response field (RF)) remained constant, while the total value (V_out, presented outside the RF) of all other alternatives was systematically varied. They showed that the neural response to the RF target was influenced by the total value of all presented alternatives, with larger overall values resulting in more significant suppression. They also showed that even in the absence of an RF target (V_in = 0, bluish lines in Figure 7C), activity was also suppressed in a context-dependent manner, with higher V_out values pushing activity levels further below baseline. Relative value coding has also been observed in human studies using electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) (Itthipuripat et al., 2015; Louie et al., 2011). It has been proposed that this form of relative value coding can be explained by divisive normalization, a fundamental neural computation observed in sensory brain regions (Carandini & Heeger, 2011; Reynolds & Heeger, 2009). Importantly, normalized value coding considers the influence of immediate context on value-based decision-making. This establishes a link between the modulation of neural coding by context and context-specific decisions.

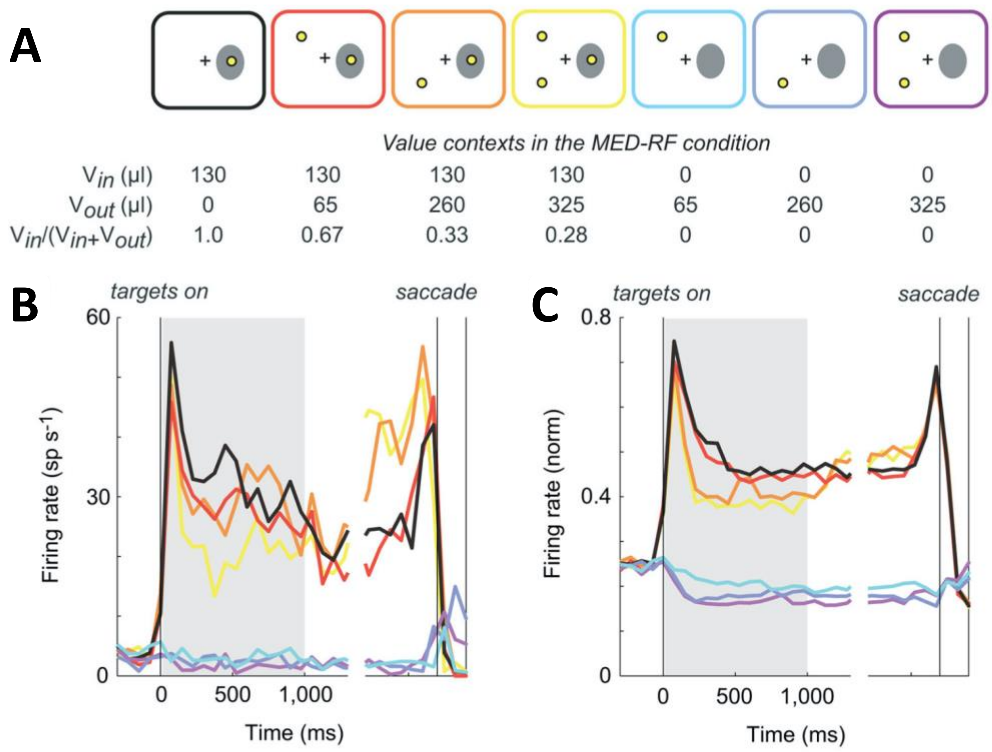

Figure 7. Immediate context-dependence value coding in LIP. **(A)** Seven possible target configurations, presented randomly on each trial. Monkeys were presented with a target array of stimuli associated with different reward magnitudes (bottom). The target value, V_in, shaded in gray, was constant, while the total value varied with the number and reward size of V_out targets. **(B)** Example of single-neuron activity in LIP. **(C)** Population average activity. In B and C, both the target-driven activity (black-yellow) and the baseline activity (cyan-violet) show a higher degree of suppression by increasing the total presented values, adapted from (Louie et al., 2011).

Temporal context-dependence

While immediate context can affect value coding instantly through normalization, value is also shaped by temporal context, defined by the sequence of rewards encountered over time. Temporal context-dependence, like immediate context effects, has been demonstrated in sensory systems (Schwartz et al., 2007). Neurons adapt not only to the average level of recent stimuli but also to properties like variance, and adjust their sensitivity based on the broader statistical structure of the environment (Kobayashi et al., 2010; Padoa-Schioppa, 2009; Padoa-Schioppa & Assad, 2008). In particular, neurons in the orbitofrontal cortex (OFC) adjust their firing based on recent reward history. Padoa-Schioppa trained monkeys to choose between two juice rewards with different reward ranges while the same neurons were recorded across sessions (Figure 8A). In Figure 8B, it shows that OFC neurons shift their response range to match the experienced distribution of reward values (Padoa-Schioppa, 2009). This suggests that the coding of value is not fixed over time either, but adapts to the history of context over time.

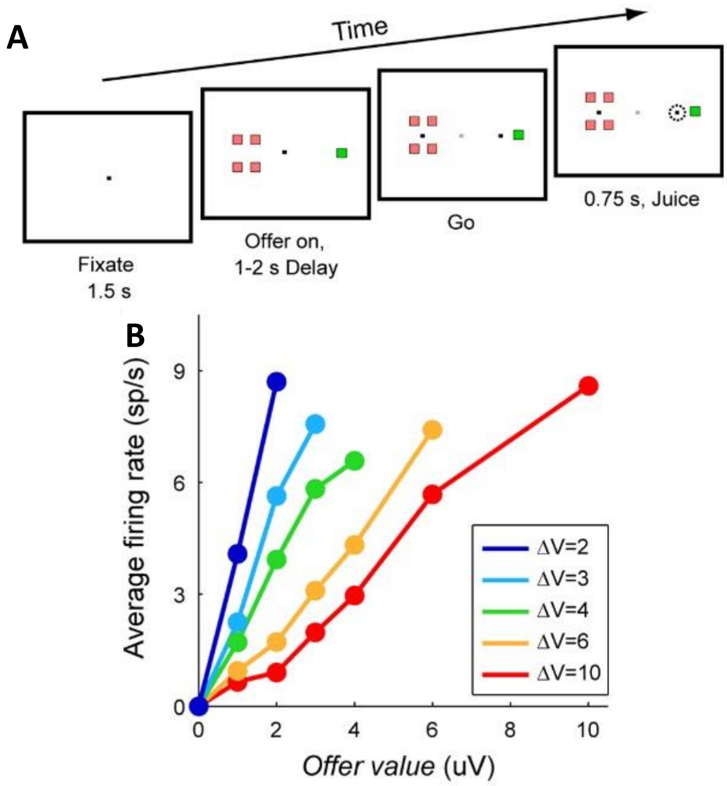

Figure 8. Temporal context-dependence value coding in OFC. **(A)** After the monkey fixated on the center of the screen, two sets of colored squares then appeared on the left and right sides of the screen; the color and the number of each set indicated the type and the quantity of juice respectively. After a random delay, when two saccade targets appeared near the offers, the monkey made its choice by shifting gaze to one of the targets. Across trials, juice quantities varied randomly for each juice pair, and the left/right positions of each offer were counterbalanced. **(B)** Average neuronal responses in OFC, each line shows the average response of a neuron for a specific range of values, adapted from (Padoa-Schioppa, 2009).

Outline of the dissertation

It is now well-established that the brain's value coding and decision-making processes are deeply context-dependent in both space and time. Our decisions in real-life scenarios often deviate from the expected path of rational choice theories. Over the past few decades, research using value-based decision-making tasks, as well as limited research using perceptual stimuli, has shown empirical findings corroborating these deviations and explaining the mechanisms underlying this sort of irrational behavior. Context effects are typically associated with decisions between multiple alternatives. These effects were initially observed in complex, multi-attribute choices, a class of phenomena known as decoy effects. Recently, however, a novel context effect was reported in single-attribute decisions, the distractor effect. Despite this progress, there is still debate about 1) the contribution of temporal vs. immediate context to the emergence of context-dependent choice behavior, and 2) the robustness and generalizability of contextual effects across domains. This dissertation aims to use well-tailored multi-alternative tasks to address these gaps. First, I used a value-based task to unravel the contribution of temporal vs. immediate contexts to the emergence of contextual effects (**Chapter 2**). More importantly, I used perceptual tasks to consider the generalizability of these effects across domains (**Chapters 3 and 4**). I employed behavioral data analysis, computational modeling, and pupil analysis to shed new light on the underlying mechanisms of these context effects.

Chapter 2 provides insights on how different contexts influence the value representation learned over time and its subsequent choice behavior. Using a well-controlled value learning task, I was able to carefully dissociate the immediate context from the temporal context. Thus, it allowed me to precisely look at the learned subject value before the decision-making stage. I then eventually extended a computational model that can capture the range of distractor effects observed in the task.

Chapter 3 focuses on the influence of immediate context dependence using perceptual stimuli. To better understand the conflicting distractor effects reported in the literature, a multi-alternative task using perceptual stimuli instead of economic values was designed. This would allow me to objectively map a single perceptual stimulus to a decision value and thoroughly investigate the influence of immediate context on decision-making. In addition, I sought to determine whether the distractor effect, previously reported in value-based decisions, generalizes to perceptual decisions. Here I also reported how global arousal influences the direction of distractor effects which is a novel finding in the scope of context dependent decision-making.

Chapter 4 presents the replication of well-known decoy effects using a new task paradigm with perceptual stimuli. The data in this chapter come from a large magnetoencephalography (MEG) dataset with pharmacological manipulation. The main purpose of this dataset is to investigate information sampling that results in various context effects. Here, I only analyzed the behavioral and eye data to demonstrate how these multiattribute context effects are interconnected. I also assessed pupil response as an indicator of internal arousal to determine whether global arousal impacts these complex biases. The results in this chapter provide new insights into the internal and external factors that yield context effects.

Extended Data

Figure S1. QR code directs to ChatGPT, which answer the question, "*how many decisions do we make every day?*"

2 | Temporal context-dependence during human value-learning

Summary

Contrary to the predictions of normative theories, choices between two high-value alternatives can be biased by the introduction of a third low-value alternative (dubbed the distractor effect). Normalization-based theories, like divisive and range normalization, explain different forms of the distractor effect by suggesting that the value of each alternative is normalized by a summary statistic of the values encountered in a particular decision context. The decision context can include alternatives encountered over an extended timeframe (temporal context); and alternatives that are available for choice on a given instance (immediate context). To date, the extent to which the immediate and temporal context (co-) shape context-dependent value representations remains unclear. To investigate this, we designed a task in which human participants (onsite: N = 30, online: N = 68) learned the values associated with three different alternatives and provided explicit value estimates before making a series of choices among ternary and binary combinations of those alternatives. We show that context-dependence already emerges in the pre-choice value estimates and is equally present in binary and ternary choice trials. Based on these findings, we conclude that the temporal (and not the immediate) context modulates subjective value representations. Interestingly, the direction and across-participants variability of this modulation we report runs against both divisive and range normalization theories. Instead, our data are best explained by a stochastic rank-based model, according to which the value of an alternative is distorted by a series of memory-based binary comparisons with previously encountered alternatives.

Introduction

Does your preference between two highly desirable products (3^{rd} generation vs. 2^{nd} generation wireless earbuds) change when the seller introduces a third less desirable product (wired earbuds)? Normative theories posit that the relative preference between two alternatives should be independent of the value and the number of other alternatives that are present in the choice set (Luce, 1959, 1977). However, contrary to this premise, empirical findings have shown that the choice between a high-value (HV) and a lower-value (LV) alternative can be affected by adding a third distractor alternative (DV) whose value is lower than the lower-value (LV) alternative. This phenomenon is known as the distractor effect (Chang et al., 2019; Chau et al., 2014, 2020; Itthipuripat et al., 2015, 2015; Louie et al., 2013; Webb et al., 2020). The distractor alternative can impact choice quality either in a positive or in a negative manner. In the *positive distractor* effect the tendency choose higher-value (HV) over lower-value (LV) increases as the value of the choose higher-value (HV) over lower-value (LV) increases (Chang et al., 2019; Chau et al., 2014, 2020). By contrast, in the *negative distracto*r effect a higher distractor value (DV) reduces the tendency to choose higher-value (HV) over lower-value (LV) alternative (Itthipuripat et al., 2015; Kohl et al., 2023; Louie et al., 2013; Webb et al., 2020, 2021).

Distractor effects challenge the independence from irrelevant alternatives principle (IIA) (Luce, 1959, 1977) and pose constraints on the underlying mechanisms that mediate valuation and choice. Random utility models, that apply noise on veridical (unaffected by the context) representations of choice alternatives, predict either a null distractor effect (i.e., logit models) or a feeble positive distractor effect (i.e., probit models, Figure 1B, left) (Berkowitsch et al., 2014; Greene, 2000; Kropko, 2008; Paetz & Steiner, 2018). However, more sizable distractor effects, akin to those seen in experimental datasets, cannot be captured by random utility models. Instead, stronger distractor effects necessitate mechanisms that distort the values of the alternatives based on quantities that relate to the values encountered in a given context (Holper et al., 2017; Khaw et al., 2017; Louie & De Martino, 2014; Rangel & Clithero, 2012; Rigoli, 2019; Webb et al., 2021).

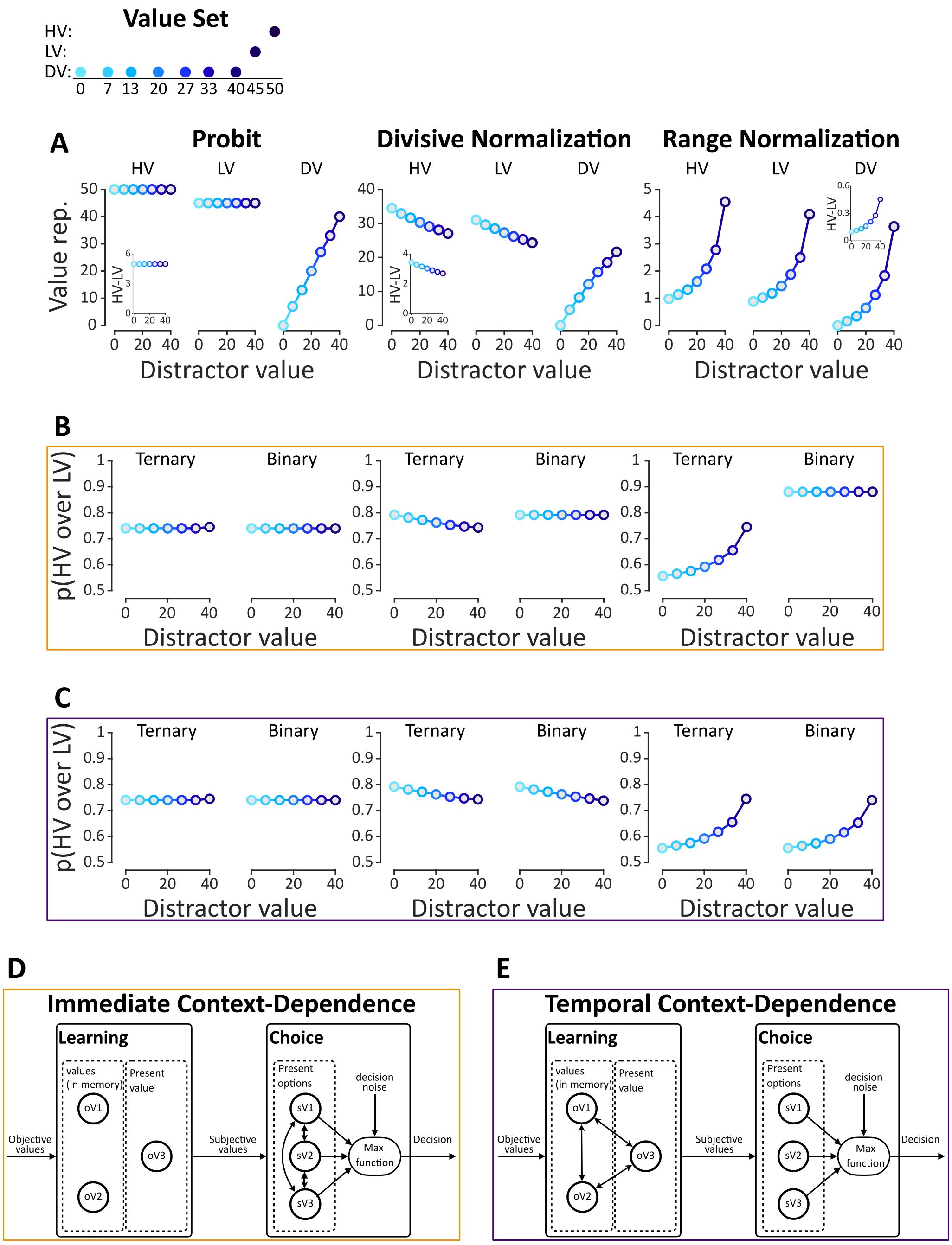

Figure 1. Computational models and predictions. (A) Value representations for each alternative by probit (left), divisive normalization (middle) and range normalization (right) models. The high-value (HV) and lower-value (LV) alternatives were kept fixed and the distractor value (DV) changed. As the distractor value increases the probit model maintains a constant value for two high-value alternatives (HV and LV), a divisive normalization model predicts a decrease of HV and LV values, and a range normalization predicts an increase of HV and LV values. The embedded plots depict the difference between the value representation of HV and LV as a function of the distractor value. **(B)** Simulated relative choice of HV over LV in the "immediate-context" framework and **(C)** "temporal-context" frameworks. In each subplot, *P(HV over LV)* is calculated separately for ternary (HV, LV, DV) and binary choice trials (HV, LV). **(D)** Visual depiction of the immediate and **(E)** temporal context-dependence frameworks. The two-sided arrows indicate computations leading to context-dependent distortions between alternatives. One-sided arrows indicate the transfer of information to the corresponding node.

Context-dependent value distortion has been associated with neurobiological constraints and the premise that neuronal firing adapts to the characteristics of the stimuli in the context in order to maximize the efficiency of the neural code (Louie et al., 2011; Louie & De Martino, 2014; Louie & Glimcher, 2012; Soltani et al., 2012). In particular, in the range normalization model, each alternative value is divided by the range of all values (i.e., maximum *minus* minimum) in the current context (Kontek & Lewandowski, 2018; Palminteri et al., 2015; Parducci, 1965; Soltani et al., 2012). Therefore, when the context features a higher distractor value, it leads to a narrower range or normalization term. This gives rise to a higher distorted value (i.e., subjective value) for both of the two high-value alternatives (Figure 1A, right), and a greater difference between them (Figure 1A, right, embedded plot), effectively leading to a positive distractor effect (Figure 1B, right). By contrast, in the divisive normalization model, each value is normalized by the sum of all values in the context (Louie et al., 2013; Louie & De Martino, 2014; Rangel & Clithero, 2012). Thus, a higher distractor value results in a larger normalization term, dwarfing both the distorted values for the two high-value alternatives (Figure 1A, middle) and the value difference between them (Figure 1A, middle, embedded plot). Consequently, this type of distortion gives rise to a negative distractor effect (Figure 1B, middle).

Despite the recent proliferation of experimental studies and the development of normalization models focusing on context-dependence, definitive conclusions on the underlying mechanisms remain elusive (Cao & Tsetsos, 2022a; Chau et al., 2020; Gluth et al., 2020; Hayes & Wedell, 2023a; Juechems et al., 2022; Louie et al., 2013). First, there are controversies around the exact direction and robustness of distractor effects. Specifically, both positive (Chau et al., 2014, 2020; Gluth et al., 2018) and negative (Itthipuripat et al., 2015; Louie et al., 2013) distractor effects have been reported using different experimental paradigms ranging from reward-learning in primates to risky and preferential choice paradigms in humans. Some of these effects failed to replicate (Gluth et al., 2018, 2020) or changed direction after re-analysis (Cao & Tsetsos, 2022a; Chau et al., 2020). Second, previous studies have not systematically examined the timescale in which context-based distortions operate. Value representations could be distorted on the basis of the values of alternatives that were previously encountered (temporal context, Figure 1E); and also, on the basis of the values of the alternatives that are immediately available on a given choice trial (immediate context, Figure 1D) (Frydman & Jin, 2022; Louie & De Martino, 2014; Madan et al., 2021). It is worth mentioning that some context effects arise in one-shot decisions embedded in non-specific temporal contexts (Chau et al., 2014; Gluth et al., 2018, 2020; Louie et al., 2013). In these cases, the immediate context account is the only viable one. However, in tasks that involve learning the values of alternatives within specific temporal contexts (i.e., with each context being characterized by a different distractor value) and subsequently making choices based on these learned values (i.e., subjective values), the distinction between temporal and immediate context is blurry (Bavard et al., 2021; Bavard & Palminteri, 2023; Hayes & Wedell, 2023a; Louie et al., 2013; Palminteri & Lebreton, 2021). The key experiments that could differentiate the influence of the immediate context from that of the temporal context in value-learning tasks are yet to be conducted.

Driven by the above, we here probed distractor effects within a single experimental paradigm that does not tap upon complex cognitive processes evoking alternative interpretations for distractor effects (Chau et al., 2014, 2020). In particular, we used a simple value-learning task previously shown to induce a negative distractor effect in primates (Louie et al., 2013). Like in previous studies, to assess the magnitude of the distractor effect, we varied the value of the distractor alternative (DV) across contexts (experimental mini-blocks). Our design differed from previous studies (Cao & Tsetsos, 2023; Itthipuripat et al., 2015) in the following aspects. First, in our task, the reward values associated with each alternative were independently learned before the choice phase. Second, we interleaved a value estimation task immediately after the learning phase so that we could directly gauge people's subjective values before the onset of the choice phase. That way we could ask whether value distortions had already occurred at the end of the learning epoch, which would support the temporal context hypothesis (Figure 1C and 1E). Finally, in the choice phase we interleaved binary and ternary choice trials. Comparing the relative choice of higher-value (HV) over lower-value (LV) in these two trial types, we could assess the extent to which the immediate availability of the distractor alternative affects choice (Figure 1B and 1D, immediate context hypothesis).

To outline our results, in two experiments (onsite and online) we report that value distortions operate on a longer timescale (i.e., the temporal context) while the immediate context had no effect. Specifically, we found that subjective value estimates (elicited in the value estimation phase, interchangeably referred to as estimated values) predicted well the choice rates; and that choice rates were undifferentiated in binary (distractor absent) and ternary (distractor present) trials. Focusing on the pre-choice phase, the higher-value (HV) and lower-value (LV) estimated values were smaller in high distractor contexts, which is consistent with the divisive normalization model. Although the difference between higher-value (HV) and lower-value (LV) was, on average, marginally smaller in high distractor contexts (a weak negative distractor effect), which is also consistent with divisive normalization, a large portion of participants showed a positive distractor effect that runs against divisive normalization. Inspired by the decision-by-sampling framework (Noguchi & Stewart, 2018a; Stewart et al., 2006), we describe a stochastic rank-based mechanism that predicts value reduction in high distractor contexts while also accounting for the individual variability in the distractor effect (both positive and negative distractor effects across different participants). Taken together, our results shed new light on the timescale and computational mechanisms that underlie context-dependent multi-alternative choices.

Results

We collected data from N = 30 (onsite in Experiment 1) and N = 68 (online in Experiment 2) human participants performing a value-learning task (Figure 2, see Materials and Methods). Participants were instructed to complete 48 mini-blocks of a color-reward association task. Their task was to collect valuable-colored coins to maximize their overall obtained reward. Each mini-block started with a learning phase where participants learned the association between colored coins and reward-values. Later, they faced binary and ternary choices in the choice phase, aiming to choose the alternative (colored coins) with the highest reward. Following the learning and choice phases we added two estimation phases, in which participants reported their subjective value estimates for each colored coin (Figure 2A). In each mini-block, the value of all three alternatives (i.e., the context) was kept fixed. We randomly assigned the 3 alternatives to 3 colored circles (red, blue, and yellow), mapping them onto 3 imaginary coins of different values. In total, we created 4 unique contexts, fully counterbalanced across the reward-color mappings, repeated 12 times each. These 4 contexts were produced by deploying two levels of distractor DV = {18, 40} allowing us to assess the distractor effect, and two magnitude levels to insert variability into the task HV = {55, 50}, LV = HV - 5. The magnitude level (HV equal to 55 or 50) did not yield any significant effects in any of the key analyses. Therefore, for the sake of simplicity, we collapsed the data across the two magnitude levels.

Task description and basic performance

During the learning phase (Figure 2B), participants were sequentially exposed to the value associated with each alternative. The value was shown by a cloud of moving dots, with the number of dots representing the reward magnitude (i.e., number of points) associated with the coin (see Materials and Methods). Participants completed 99.91% (95% CI = [99.84%, 99.97%]) of all learning trials with an average reaction time of 623.66 milliseconds (ms) (95% CI = [593.56 ms, 653.76 ms]) in Experiment 1, and 99.3% (95% CI = [98.94%, 99.66%]) of all learning trials with an average reaction time of 411.92 (ms) (95% CI = [386.66 ms, 437.18 ms]) in Experiment 2, indicating that they properly engaged with the learning phase. We did not see any differences between the reaction times across learning trials that involved the HV, LV, and DV alternatives across different contexts in either experiment (2-way ANOVA on *log*(RT) in Experiment 1: alternatives: $F(2,179) = 0.004$, $p = 0.99$, contexts: $F(1,179) = 0.15$, $p = 0.69$, interaction: $F(2,179) = 0.02$, $p = 0.98$; and in Experiment 2: alternatives: $F(2,407) = 0.03$, $p = 0.97$, contexts: $F(1,407) = 0.06$, $p = 0.81$, interaction: $F(2,407) = 0.04$, $p = 0.97$).

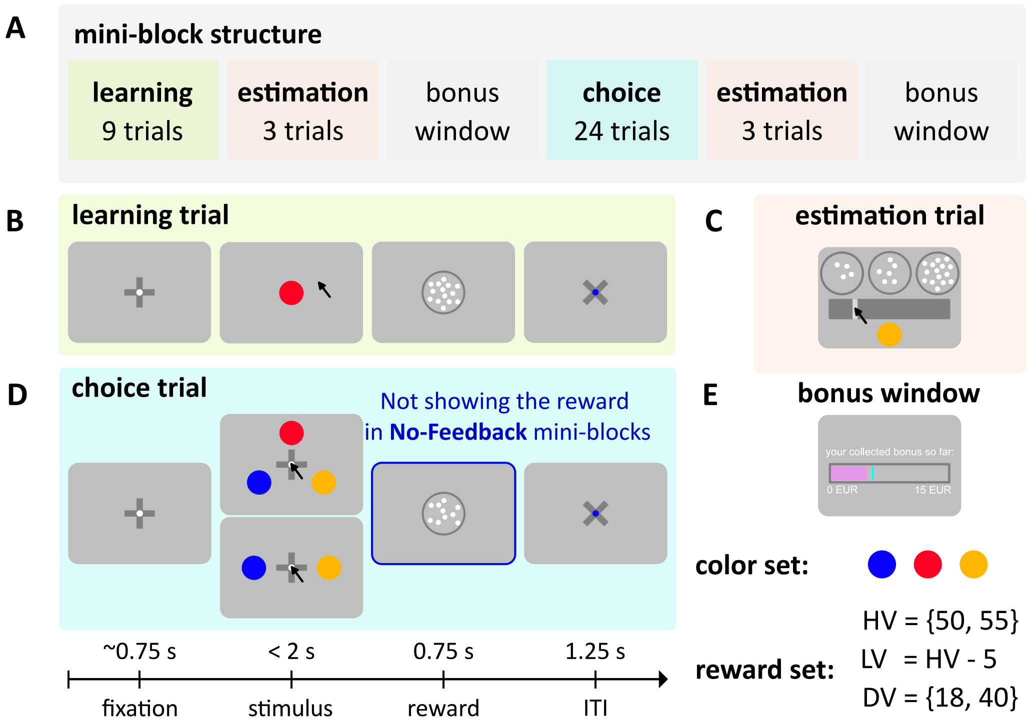

Figure 2. Human value learning task. (A) Mini-block timeline (from left to right), each participant completed 48 mini-blocks of color-reward association task. They were instructed to maximize their total obtained reward by first learning the color-reward association during the learning phase of each mini-block and then choosing the alternative with the highest reward in the subsequent choice phase. Each mini-block started with the learning phase where participants sequentially observed the values associated to three alternatives (imaginary colored coins, look at the color set) in a given context. Each context included a unique HV, LV, and DV alternative (c.f. reward set). Following the learning phase, each mini-block continued with the first estimation phase where participants reported their subjective value estimate of each alternative. After the estimation phase, the bonus window shortly appeared before the choice phase began. In the choice phase, participants had to choose the alternative that yielded the largest reward. The choice phase was followed by the second estimation phase and each mini-block ended with the presentation of the final bonus window. **(B)** The learning phase consisted of 9 learning trials (3 per each alternative). Each trial began with the fixation cue for a random duration, and after that one of the alternatives appeared on the screen. Participants were asked to click on the alternative within 2 seconds to get the associated reward (i.e., represented by the number of a set of moving dots). **(C)** The Estimation phase involved 3 trials (1 per each alternative). On each trial, an alternative was presented below a slider bar and participants were asked to move the slider to indicate the number of dots (i.e., reward value) associated with that alternative. **(D)** The choice phase included 24 trials (12 ternary and 12 binary). Like learning trials, each choice trial initiated with the fixation cue for a random delay, and after that, 2 or 3 alternatives presented on the screen. Participants were asked to click on their preferred alternative within 2 seconds to see the collected reward. In "No-Feedback" mini-blocks, the choice was immediately followed by the inter-trial-interval (ITI) window, and the collected reward was not presented. **(E)** The bonus window, presented after each estimation phase, revealed the participant's collected monetary bonus in a pink bar and the possible maximum collected bonus with a cyan line so far. All panels are based on Experiment 1, the design of both experiments was identical, the only minor change in the online experiment was the use of keyboard instead of mouse clicks to record participants' responses at each phase. Note that the panels are a schematic (cartoon) of the trials, for exact details of the stimuli and reward, see Materials and Methods.

In the choice phase (Figure 2D), participants made 12 ternary and 12 binary choices (four trials per each possible binary pair) by reporting their preferred alternative within a maximum of two seconds. We included all three possible binary pairs (HV vs. LV, HV vs. DV, LV vs. DV) to keep the presentation rate of all alternatives equal and to avoid introducing any implicit bias toward the two high-value alternatives. Participants completed 99.73% (95% CI = [99.62%, 99.84%]) of all choice trials with an average reaction time of 729.89 (ms) (95% CI = [695.14 ms, 764.65 ms]) in Experiment 1, and 99.34% (95% CI = [99.08%, 99.60%]) of choice trials with an average reaction time of 614.50 (ms) (95% CI = [581.55 ms, 647.45 ms]) in Experiment 2. Participants chose the best alternative significantly higher than the chance level in both ternary and binary trials (Experiment 1: accuracy in ternary = 81.63% (95% CI = [78.49%, 84.77%]), $t(29) = 30.17$, $p < 0.001$, and in binary = 90.27% (95% CI = [88.29%, 92.25%], $t(29) = 39.86$, $p < 0.001$; Experiment 2: accuracy in ternary = 70.08% (95% CI = [66.81%, 73.35%]), $t(67) = 22.03$, $p < 0.001$, and in binary = 81.23% (95% CI = [78.66%, 83.81%], $t(67) = 23.80$, $p < 0.001$; Figure S1 in Extended Data). The average reaction time in binary trials was significantly higher than in ternary trials only in Experiment 1 and did not change across different contexts in both experiments (2-way ANOVA on *log*(RT) in Experiment 1: choice type: $F(1,119) = 11.40$, $p < 0.001$, contexts: $F(1,119) = 0.20$, $p = 0.65$, interaction: $F(1,119) = 0.03$, $p = 0.87$; and in Experiment 2: choice type: $F(1,271) = 2.97$, $p = 0.09$, contexts: $F(1,271) = 0.93$, $p = 0.34$, interaction: $F(1,271) = 0.01$, $p = 0.92$; Figure S1 in Extended Data). This seemingly counterintuitive finding might be attributed to the greater uncertainty linked with the identities of the alternatives in binary trials.

Moreover, in half of the mini-blocks, we withheld reward feedback in the choice phase to intercept further learning from feedback after the value estimation phase. Withholding feedback could help us better quantify immediate context effects. We found no statistically significant evidence that receiving feedback improved choice accuracy in Experiment 1 (choice accuracy pooled across both ternary and binary: in "Feedback", 89.00% (95% CI = [86.25%, 91.76%]) and in "No-Feedback", 87.22% (95% CI = [85.02%, 86.42%]) mini-blocks; two-sided *t*-test: $t(29) = 1.54$, $p = 0.13$). However, in Experiment 2, accuracy was significantly higher in the Feedback condition (choice accuracy pooled across both ternary and binary: in "Feedback", 79.69% (95% CI =

[77.14%, 82.25%]) and in "No-Feedback", 77.19% (95% CI = [74.11%, 80.27%]) mini-blocks; two-sided *t*-test: $t(67) = 3.20$, $p < 0.01$). There was no statistically significant difference in the average reaction time between receiving and not receiving feedback in both experiments (reaction time pooled across both ternary and binary in Experiment 1: "Feedback", 730.46 (ms) (95% CI = [696.85 ms, 764.07 ms]) and "No-Feedback", 729.36 (ms) (95% CI = [691.98 ms, 766.75 ms], two-sided *t*-test on *log*(RT): $t(29) = 0.39$, $p = 0.70$); in Experiment 2: "Feedback", 609.23 (ms) (95% CI = [576.25 ms, 642.29 ms]), and "No-Feedback", 619.84 (ms) (95% CI = [585.92 ms, 653.76 ms]) mini-blocks; two-sided *t*-test on *log*(RT): $t(67) = -1.40$, $p = 0.17$). Overall, the choice rate (i.e., the number of times one alternative is chosen *divided by* the number of times that alternative is presented) of each value was consistent with value-guided decision-making (Experiment 1: choice rate of (HV) = 84.83%, (95% CI = [82.17%, 87.49%]), (LV) = 31.80%, (95% CI = [29.94%, 33.65%]), and (DV) = 3.32%, (95% CI = [2.08%, 4.56%]); Experiment 2: choice rate of (HV) = 74.31%, (95% CI = [71.33%, 77.28%]), (LV) = 35.85%, (95% CI = [34.59%, 37.10%]), and (DV) = 9.80%, (95% CI = [7.63%, 11.98%]), pooled across both "Feedback" and "No-Feedback" mini-blocks).

In the estimation phase (Figure 2C), participants were asked to report their subjectively learned value of each alternative by moving a slider on a bar within 10 seconds. Participants completed 99.70% (95% CI = [99.51%, 99.89%]) of all estimation trials across both phases with an average reaction time of 3.24 seconds (sec) (95% CI = [2.95 (sec), 3.52 (sec)]) in Experiment 1, and 98.29% (95% CI = [97.32%, 99.27%]) of them with an average reaction time of 3.31 (sec) (95% CI = [2.93 (sec), 3.69 (sec)]) in Experiment 2. In both experiments, the average estimated values (i.e., subjective values) correlated strongly with the actual values in estimation phases, (Pearson correlation in Experiment 1, First estimation: $r = 0.98$ (95% CI = [0.98, 0.99]), two-sided *t*-test on correlation coefficients: $t(29) = 334.17$, $p < 0.001$, Second estimation: $r = 0.98$ (95% CI = [0.97, 0.99]), two-sided *t*-test on correlation coefficients: $t(29) = 251.69$, $p < 0.001$; and in Experiment 2, First estimation: $r = 0.97$ (95% CI = [0.96, 0.98]), two-sided *t*-test on correlation coefficients: $t(67) = 230.94$, $p < 0.001$, Second estimation: $r = 0.96$ (95% CI = [0.95, 0.98]), two-sided *t*-test on correlation coefficients: $t(67) = 139.36$, $p < 0.001$). All analyses above indicate that participants engaged well with the estimation and choice tasks.

Context-dependent distortions during learning

Having ensured that participants complied with the task instructions, we next asked how value estimates (i.e., subjective values) varied as a function of the distractor value. Here, we analyzed the estimation data pooled across both “Feedback” and “No-Feedback” mini-blocks, as this manipulation was announced to the participants at the end of the estimation phase (see Materials and Methods). We only focused on the results from the first estimation because these were not influenced by any behavior or feedback received during the choice phase. Figure 3A and 3D show the average value estimates for each alternative across contexts. In both experiments, in the first estimation, there was a statistically significant decrease of the estimated values of the two high-value alternatives in the high-distractor context relative to the low-distractor context (two-sided t-test in Experiment 1: HV: $t(29) = 5.33$, $p < 0.001$, LV: $t(29) = 5.38$, $p < 0.001$; in Experiment 2: HV: $t(67) = 4.64$, $p < 0.001$, LV: $t(67) = 2.14$, $p = 0.036$; and pooled across both experiments; HV: $t(97) = 6.55$, $p < 0.001$, LV: $t(97) = 4.13$, $p < 0.001$). This effect indicates that distractor-induced distortions in subjective value already occurred during the learning epoch.

At first glance, this pattern appears consistent with the divisive normalization prediction and runs against the range normalization prediction (Figure 1A). Divisive normalization also predicts that the value difference between the higher-value (HV) and lower-value (LV) alternatives decreases as the distractor value (DV) increases (embedded plot in Figure 1A, middle). Figure 3E shows that the value difference between the higher-value (HV) and lower-value (LV) alternatives is in line with the prediction of divisive normalization in Experiment 2 (two-sided t-test on “*HV – LV*” between the contexts with low and high distractors, First estimation: $t(67) = 2.27$, $p = 0.026$), but Figure 3B shows that this is not the case in Experiment 1 (two-sided t-test on “*HV – LV*” between the contexts with low and high distractors, First estimation: $t(29) = -0.006$, $p = 0.99$). The latter null finding (Bayesian t-test on “*HV – LV*” between the contexts with low and high distractors, $BF_{01} = 5.14$) in the value difference is more consistent with a probit model, which however does not predict a global reduction in value estimates (embedded plot in Figure 1A, left). The difference in the “estimation” distractor effect between the two experiments could presumably be attributed to variations in the demographics of the online and onsite cohorts; or to the overall lower engagement and attention in online studies due to the different environment between lab-based and online studies (evidenced by small but consistent accuracy differences: two-sided *t*-test on overall choice accuracy of best alternative between the two experiments: $t(97) = 4.33$, $p < 0.001$).

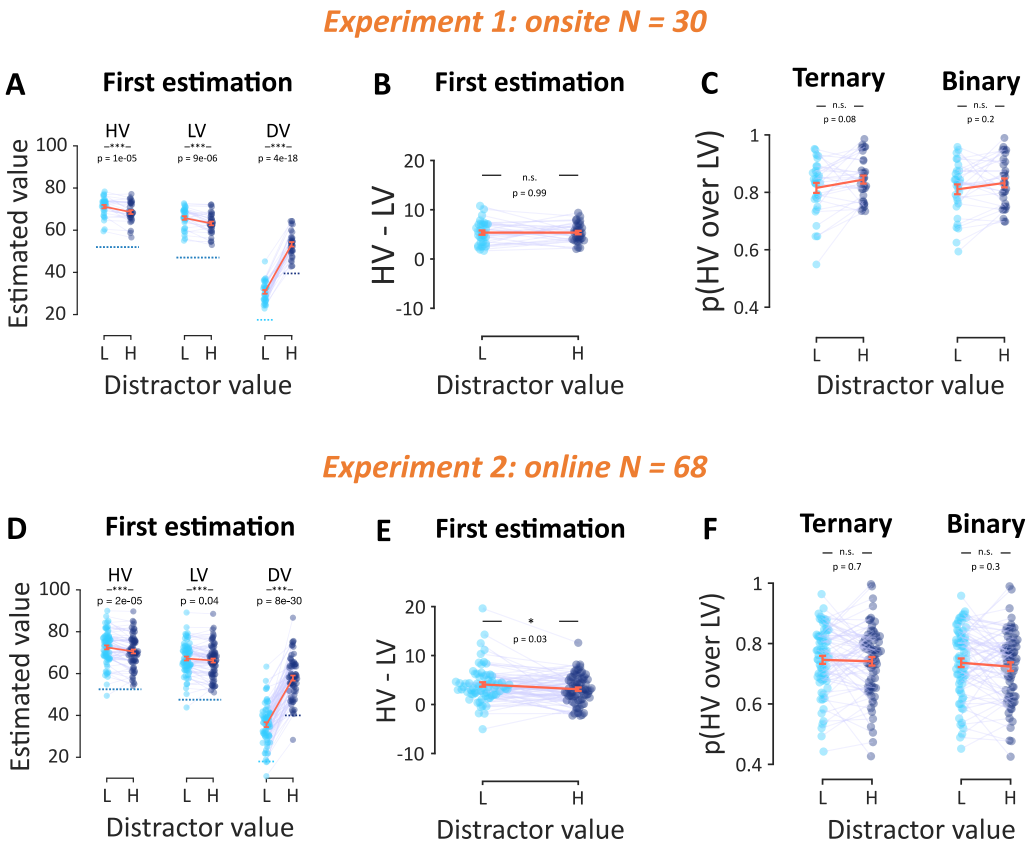

Figure 3. Context dependence in estimated value and choice. (A, D) Mean estimated value of each alternative as a function of the distractor value. Dashed lines indicate the actual values. **(B, E)** The difference in estimated values between the two high-value alternatives, shown in the two distractor contexts. **(C, F)** Relative choice of HV over LV in the choice phase as a function of the distractor value in ternary trials and binary (HV, LV) trials. In all panels, data were pooled across “Feedback” and “No-Feedback” mini-blocks, the orange error bars indicate standard errors of the mean across participants, and the colored dots indicate individual participants.

Thus, in two experiments, increasing the distractor value consistently reduced the estimated values of the two high-valued alternatives, while its effect on their difference was marginally negative (two-sided *t*-test on “*HV* – *LV*” between the contexts with low and high distractors, aggregated across the two experiments; First estimation: $t(97) = 2.04$, $p = 0.044$). We return to the interpretation of these results at a later section.

No distractor effect in the choice phase

We next sought to assess whether the choice data revealed a distractor effect. The presence of both binary and ternary trials in the choice phase allowed us to probe the origin of a potential distractor effect by focusing on the relative choice share between the two high-value alternatives (here denoted as *p*(*HV over LV*), Equation 1) and on how this quantity varies across contexts (low- vs. high-distractor) and trial type (binary vs. ternary). Here, the data is pooled across both "Feedback" and "No-Feedback" mini-blocks, given that there was no statistically significant evidence for an interaction in relative choice share between these two mini-block types (2-way ANOVA on *p(HV over LV)*, in Experiment 1: contexts: $F(1, 116) = 1.88$, $p = 0.17$, block type: $F(1, 116) = 4.42$, $p = 0.04$, interaction: $F(1, 116) = 0.09$, $p = 0.76$; and in Experiment 2: contexts: $F(1, 268) = 0.16$, $p = 0.69$, block type: $F(1, 268) = 1.33$, $p = 0.25$, interaction: $F(1, 268) = 3.11$, $p = 0.08$).

Specifically, a main effect of "context", indicating that the relative choice share changes under high-distractor values, would reveal a non-specific distractor effect. Depending on the influence of "trial-type" this effect could be attributed to a pure temporal context account (no "context" x "trial-type" interaction), a pure immediate context account (significant interaction, with the distractor effect being present in ternary trials only), or a combination of the two accounts (with the distractor effect in binary trials capturing the temporal influence and the distractor effect in ternary trials the immediate context influence).

Analysis of the relative choice share across context and trial-type did not provide statistically significant evidence for a "context" main effect, which is necessary to establish a distractor effect (Figure 3C and 3F, 2-way ANOVA on *p(HV over LV)*, in Experiment 1: context: $F(1, 116) = 2.5$, $p = 0.12$, trial-type: $F(1, 116) = 0.27$, $p = 0.61$, interaction: $F(1, 116) = 0.04$, $p = 0.83$; and in Experiment 2: context: $F(1, 268) = 0.41$, $p = 0.52$, trial-type: $F(1, 268) = 0.96$, $p = 0.33$, interaction: $F(1, 268) = 0.08$, $p = 0.77$).

Further, the non-significant "trial-type" effect (Bayesian ANOVA with $P(M) = 0.2$ for all models on *p(HV over LV)*, in Experiment 1: null model: $BF_{01} = 1.00$, context model:

BF_{01} = 1.65, trial-type model: BF_{01} = 4.56, full model with interaction: BF_{01} = 28.69; and in Experiment 2: null model: BF_{01} = 1.00, context model: BF_{01} = 6.19, trial-type model: BF_{01} = 4.74, full model: BF_{01} = 152.38) suggests that the relative choice share is indistinguishable between binary and ternary trials. This means that there was no basic immediate context value modulation, where the relative choice share would change solely due to the addition of a third alternative in the choice set, regardless of its value. The binary and ternary distractor effects (Equation 2) were strongly correlated across participants (Pearson correlation, in Experiment 1: $r_{(30)} = 0.90$, $p < 0.001$, 95% CI = [0.80, 0.95]; and in Experiment 2: $r_{(68)} = 0.92$, $p < 0.001$, 95% CI = [0.87, 0.95], Figure S1 in Extended Data) further corroborating the lack of immediate context value modulation.

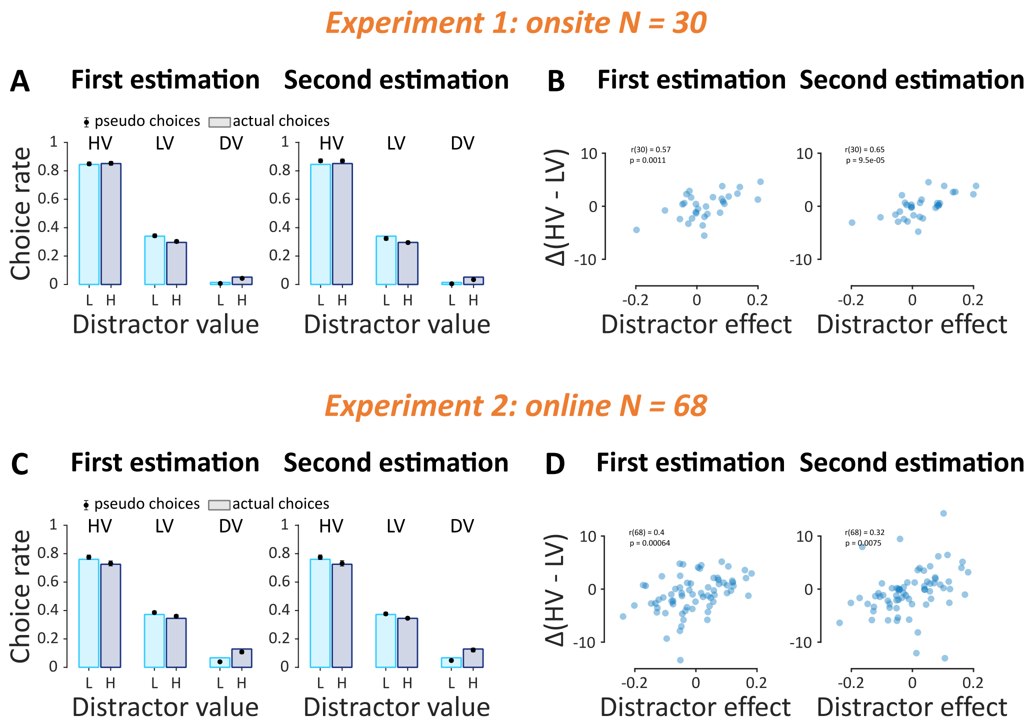

Figure 4. Value representation comparison between the estimation and choice phases. (A, C) Choice rates (bars) obtained in the choice phase and pseudo-choice rates (filled circles) derived from the estimated values (Equation 3 and 4). **(B, D)** Correlation between the distractor effect (Equation 2) and "*HV – LV*" estimate difference between two contexts. Error bars in A and C indicate standard errors of the mean across participants and in B and D the blue dots indicate individual participants.

Common value representations in estimation and choice

To recap the behavioral findings, the estimation data revealed a consistent contextual modulation, with high distractor values leading to an overall underestimation of the two high-value alternatives. There was also a weak overall reduction in the estimated value difference of the two high-value alternatives, although this was present only in Experiment 2. By contrast, the choice data did not reveal statistically significant evidence for consistent contextual modulation (2-way ANOVA on *p(HV over LV)*, aggregated across the two experiments: context: $F(1, 388) = 0.02$, $p = 0.89$, trial-type: $F(1, 388) = 1.07$, $p = 0.30$, interaction: $F(1, 388) = 0.11$, $p = 0.74$, and Bayesian ANOVA with $P(M) = 0.2$ for all models on *p(HV over LV)*: null model: $BF_{01} = 1.00$, context model: $BF_{01} = 8.86$, trial-type model: $BF_{01} = 5.32$, full model with interaction: $BF_{01} = 295.21$). Should behavioral patterns in the estimation and choice phases be interpreted within a single explanatory framework? Addressing this question requires determining whether behavioral outputs in estimation and choice were governed by common value representations.

To determine that, we examined the consistency between value estimates and choices. We applied an established approach (Equation 3 and 4 (Bavard & Palminteri, 2023)) to calculate pseudo-choices that would have been made had participants relied on the values reported in the estimation phases. We then compared the choice rate between the actual choices and the pseudo-choices. Assessing the choice rate allowed us to combine binary and ternary choices in one quantity. Figures 4A and 4C illustrate that pseudo-choices obtained from the value estimates are highly correlated with the actual choices in both experiments (Pearson correlation, in Experiment 1 with First estimation: $r = 0.994$ (95% CI = [0.991, 0.996]), two-sided *t*-test on correlation coefficients: $t(29) = 595.62$, $p < 0.001$, with Second estimation: $r = 0.992$ (95% CI = [0.987, 0.998]), $t(29) = 363.69$, $p < 0.001$; and in Experiment 2 with First estimation: $r = 0.96$ (95% CI = [0.93, 0.98]), $t(67) = 66.75$, $p < 0.001$, with Second estimation: $r = 0.93$ (95% CI = [0.89, 0.98]), $t(67) = 37.94$, $p < 0.001$). We further correlated the "*HV – LV*" difference between the two contexts from the first estimation phase against the distractor effect (Equation 2) quantified in the choice phase, after combining binary and ternary choice trials (Figures 4B and 4D, Pearson correlation between the two quantities in Experiment 1 using the First estimation data: $r_{(30)} = 0.57$, $p < 0.01$, 95% CI = [0.26, 0.77], and the Second estimation data: $r_{(30)} = 0.65$, $p < 0.001$, 95% CI = [0.38, 0.82]; and in Experiment 2 the First estimation data: $r_{(68)} = 0.4$, $p < 0.001$, 95% CI = [0.18, 0.59], and the Second estimation data: $r_{(68)} = 0.32$, $p < 0.01$, 95% CI = [0.09, 0.52]). This significant correlation, in conjunction with the pseudo-choices analysis above, indicates a non-negligible link between the value estimates and choices. These results motivate us to develop a single model in the next section that can jointly explain the behavioral patterns obtained in the estimation and choice phases. We note in passing that, despite the significant correlations between the estimation and choice distractor effects—which establish that the value representation is common across the two tasks—choices may introduce small systematic shifts in the direction of the effect. Such shifts could be induced via reinforcement learning mechanisms (Cao & Tsetsos, 2023) owing to the dwarfed value representations in the high-distractor context, which is known to affect choice accuracy (Pirrone et al., 2022; Shevlin et al., 2022). Choice-induced effects of this type could perhaps explain why the marginal negative distractor effect in estimation disappears in choices in Experiment 2. However, assessing these subtler patterns is beyond the scope of this study.

Context-dependent beyond normalization theories

Taken together, across two experiments, the value estimates of the two high-value alternatives were consistently reduced as the value of the distractor alternative increases (Figures 3A and 3D). Regarding the distractor effect (i.e., the difference in value estimates or, equivalently, the relative choice share as a function of distractor value) there were considerable individual differences in the direction of the effect (Figures 4B and 4D).

Divisive normalization can account for the overall value reduction and for participants who exhibited a negative distractor effect, but it fails to capture those with a positive distractor effect. Range normalization cannot capture the overall value reduction effect and can only capture participants with a positive distractor effect. A successful model should be able to produce an overall value reduction and, depending on parameter values, account for both positive and negative distractor effects.

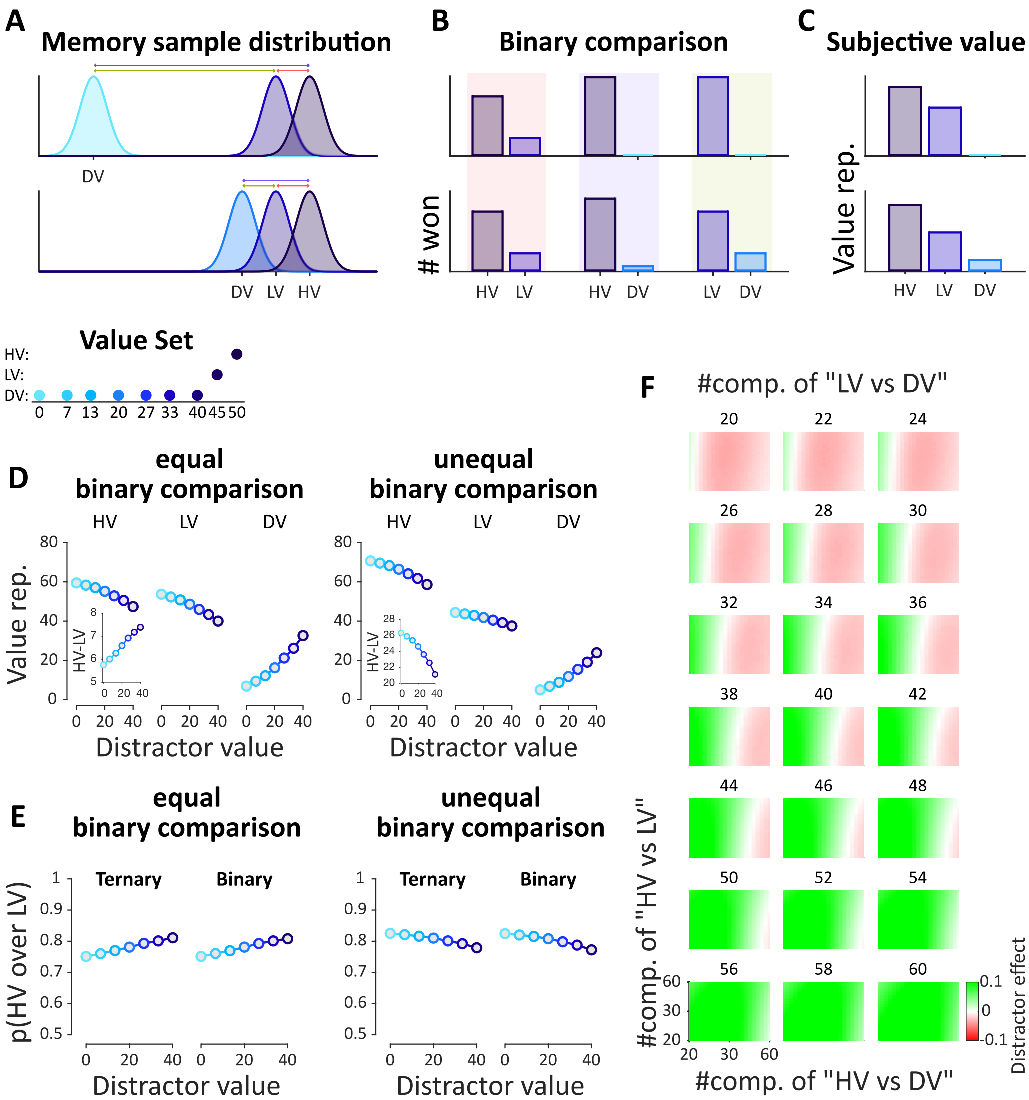

Figure 5. Rank-based (RB) model illustration. **(A)** The distribution of memory samples of the objective values. The top and bottom row are in the presence of a low and high value distractor respectively. **(B)** The schematic of number of times an alternative won in arbitrary 100 binary comparisons (*k* parameter in the RB model), here all possible binary comparisons were presented. For example, in the bottom row the HV once compared with LV (indicate by red arrow/shade) and once with DV (indicate by purple arrow/shade). **(C)** The final value representation of each alternative. Here for example the value of HV is the sum of the number of times HV won against LV and DV. **(D)** Value representations for each alternative in RB when number of binary comparison (*k* parameter in the RB model) is equal for all pairs in left and when it is unequal, here $k_{HVvsLV} > k_{HVvsDV} > k_{LVvsDV}$. Like Figure 1, the high-value (HV) and low-value (LV) alternatives were kept fixed and the distractor value (DV) changed. In both conditions, as the distractor value increases the RB model predicts a decrease of HV and LV values. The embedded plots depict that the difference between the value representation of HV and LV increases in the equal condition and decreases in the unequal condition. **(E)** Simulated relative choice of HV over LV in the "temporal context" framework. In each subplot, *P(HV over LV)* is calculated separately for ternary (HV, LV, DV) and binary choice trials (HV, LV). **(F)** Simulating distractor effect as the function of number of binary comparisons for each pair, in each panel y axis is the number of HV vs LV comparison, x axis is the number of HV vs DV comparison and the title is the number of LV vs DV comparison (for further details, see Model simulations in Materials and Methods and Figure S2 in Extended Data).

We propose a rank-based (RB) model (Stewart et al., 2006) that can capture these patterns in both estimation and choice data. This model relies on the decision-by-sampling framework that has been successfully used to predict context effects in various settings, including multi-alternative and multi-attribute choices (Noguchi & Stewart, 2014; Paetz & Steiner, 2018; Stewart et al., 2006). The rank-based (RB) model assumes that the value representation of an alternative following the learning phase is constructed via a series of stochastic binary comparisons between memory samples of the target and of previously encountered alternatives (Figure 5A and 5B). The constructed value of a target alternative is simply the number of times it won in these binary comparisons (Figure 5C). The relative reduction of higher-value (HV) and lower-value (LV) changes as a function of the number of binary comparisons made between each of the three possible pairs. Figure 5D shows that a balanced number of binary comparisons across all pairs increases "*HV – LV*" (Figure 5D, left, embedded plot) when the distractor is higher, giving rise to a positive distractor effect. This is because the lower-value (LV) alternative, being closer to the distractor value, receives stronger competition from the distractor value than the higher-value (HV) does. This larger penalty the lower-value (LV) pays can be reversed when the *LV* vs. *DV* binary comparison is the least frequent one. In this unbalanced case "*HV – LV*" decreases (Figure 5D, right, embedded plot) when the distractor is higher, giving rise to a negative distractor effect. In both the balanced and unbalanced cases, the constructed values are overall reduced for both high-value alternatives (HV and LV) due to increased competition with the distractor value (DV) in the high-distractor context (Figure S2 Extended Data).

We fitted rank-based (RB) model and the other models depicted in Figure 1 to the choice data from both experiments. As shown in Figures 1 and 5, each of the models gives rise to different value representations as a function of the distractor value. Given the lack of immediate context effects in the choice phase, these value representations are assumed to have taken shape by the end of the learning phase; and are probabilistically translated onto choices via a context-independent choice function (i.e., a probit, Equation 5) in both binary and ternary trials. Figure 6A depicts that the rank-based (RB) model provided a closer approximation to the choice distractor effect pooled across both experiments (Figure S3 in Extended Data for each Experiment) relative to the other models; we show this visually by simulating choices using the best-fitted parameters of each model, and then pooling the model predictions across both ternary and binary choices given that there was no difference in the distractor effect between ternary and binary choices. In particular, the rank-based (RB) model is the only model that captures both negative and positive distractor effects. Two further model comparisons confirmed formally that the rank-based (RB) model accounted for the choice data better than the alternative models (Figure 6B and 6C). First, in a fixed-effects comparison, the rank-based (RB) model has the smallest difference relative to the best-individualized model (ΔBIC > 10 (Kass & Raftery, 1995)) across both experiments (RB, Pr, and RN had the smallest BIC for 53.3%, 2%, and 26.7% of the participants in Experiment 1, and for 64.7%, 0.03%, and 32.3% of the participants in Experiment 2). Second, in a random-effects model comparison, the rank-based (RB) model is better supported (*P*pexc > 0.99 (Rigoux et al., 2014)) in both experiments. Note that the rank-based (RB) model can describe the relative choice of higher-value over lower-value (Equation 1) well in ternary and binary trials as we expected (two-sided paired *t*-test on predicted *p(HV over LV)* in Ternary: $t(97) = -0.87$, $p = 0.39$, and Binary: $t(97) = -0.22$, $p = 0.83$, Figure S3 in Extended Data for each Experiment).

Figure 6D shows that the rank-based (RB) model predicts a large decrease in the estimated values of the two high-value alternatives (HV and LV) as the distractor value increases (DV), equivalent to what we observed in the behavioral data (Figure 3A). In Figure 6E, we demonstrate how rank-based (RB) can capture the positive and negative distractor effect as a function of the distribution of binary comparisons across the different pairs. Here we looked at the fitted parameters k (Equation 9) for participants showing negative (with DE lower than median) and positive (with DE lower than median) distractor effects, in left and right panels respectively. Consistent with the qualitative predictions of the model depicted in Figure 5, Figure 6E shows a significant imbalance in the distribution of binary comparisons (1-way ANOVA: $F(2, 144) = 5.32$, $p < 0.01$) for the group of participants with negative distractor effect; and a balanced distribution (1-way ANOVA: $F(2, 144) = 0.87$, $p = 0.42$) for the group of participant with positive distractor effect (Table S1 and Figure S4 in Extended Data for the fits of the other models and the best-fitted parameters of all models). Thus, the rank-based (RB) model can reconcile an overall value reduction with negative or positive distractor effects in estimation (and consequently in choice, Figure 6F) under a single mechanism (Figure S2).

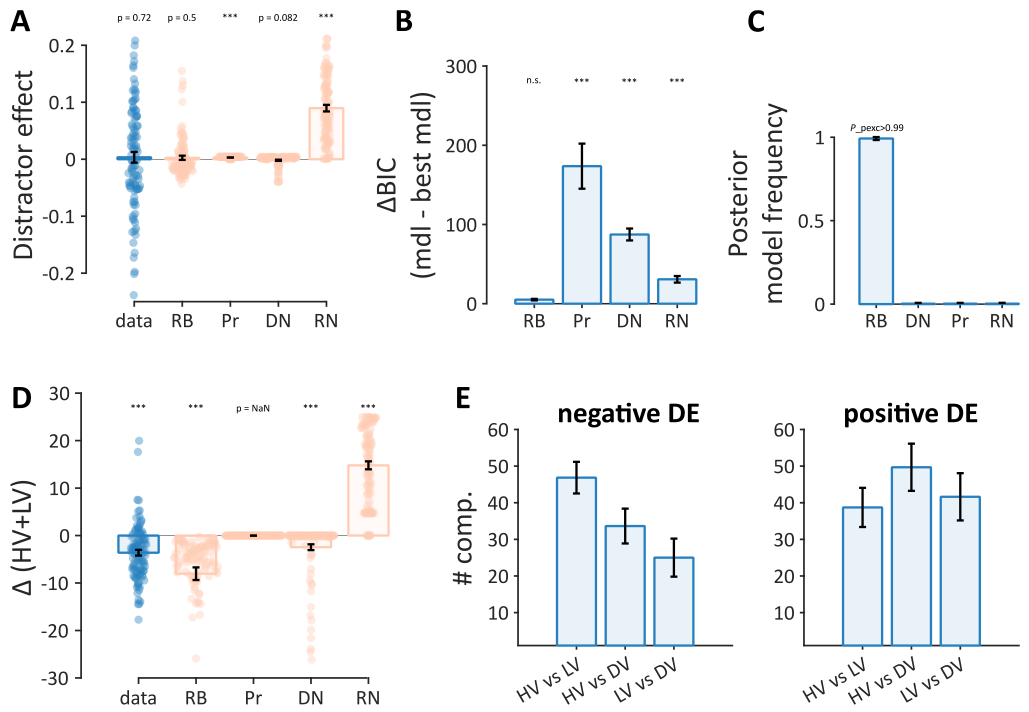

Figure 6. Model comparison. Distractor effect comparison between the actual data and simulated data using the best-fitted parameters, the RB model has a closer fit to the actual distractor effect in the choice data. **(B)** Fixed-effect Bayesian model comparison, Black asterisks: significant ΔBIC against 10, one-sided one-sample *t*-tests (Kass & Raftery, 1995). **(C)** Random-effect Bayesian model comparison (Daunizeau et al., 2014). **(D)** The difference of "*HV + LV*" between two contexts, simulated by the best-fitted parameters of the RB model. **(E)** Number of binary comparisons (best fitted *k* parameters in RB model) for two groups of participants with negative and positive distractor effect. In all panels, the data here is pooled across both experiments (N = 98) (Figure S3 in Extended Data for each Experiment), the error bars are standard errors of the mean across participants, and the colored dots indicate the individual participant.

Discussion

Previous findings suggest that the value of an inferior alternative influences choices between two high-value alternatives– a class of phenomena known as distractor effects (Chau et al., 2020; Louie et al., 2013; Louie & Glimcher, 2012). However, previous research did not specify the timescale of the distractor influence. Does the value of the inferior (distractor) alternative influence value representations at a short timescale (narrowed to a single decision), at a long timescale (spanning several decisions), or at both short and long timescales? (Frydman & Jin, 2022; Louie & De Martino, 2014; Madan et al., 2021) In addition to this knowledge gap, both positive and negative distractor effects have been previously reported (Chau et al., 2020; Gluth et al., 2020; Itthipuripat et al., 2015; Louie et al., 2013), raising questions about the generality and robustness of distractor effects. In the present study, we used a simple value-learning task to shed light on the timescale and functional form of the distractor effect.

Using a value-learning paradigm that was previously shown to induce a negative distractor effect in primates (Louie et al., 2013), we revealed an average null effect with considerable individual variability in its direction in human choices. We observed equivalent variability when quantifying the distractor effect using the value estimates participants provided immediately after the learning phase. The estimation data further revealed a consistent distortion, characterised by an overall reduction of value for the two high-value alternatives in high-distractor contexts. Further, we found that choice behavior was indistinguishable between binary (distractor absent) and ternary trials (distractor present), indicating that changes in the immediate choice context have no impact on behavior. Taken together, these findings suggest that the influence of the distractor alternative is situated in the broader temporal context, and varies in direction across individuals but remains consistent within individuals. Importantly, the distractor influence on value representations did not align with either positive or negative distractor effects. Instead, we found that the distractor value exerted a global subtractive influence on the two high-value alternatives (HV and LV); as we reported in the targeted analysis the value representations in the estimation and choice tasks were common. Consequently, we posit that it is plausible to assume a common value distortion mechanism in both choice and estimation. We formalized this mechanism using a stochastic rank-based model, inspired by decision-by-sampling theory (Bhui & Gershman, 2018a; Noguchi & Stewart, 2018a; Stewart et al., 2006).

Context effects, violating the independence from irrelevant alternatives principle, have been widely reported in psychology and behavioral economics in various domains including multi-attribute consumer choices (Dumbalska et al., 2020; Huber et al., 1982a; Webb et al., 2021) and risky choices 2020 (Mohr et al., 2017; Soltani et al., 2012). Typically, these violations are obtained in single-shot decisions, where participants have to compute the value of novel alternatives (based on some externally determined criteria) on a single trial basis. Distractor effect, which is a certain type of context effects, have been reported both in single-shot decisions (Bavard & Palminteri, 2023; Cao & Tsetsos, 2023; Gluth et al., 2018, 2020; Itthipuripat et al., 2015; Louie et al., 2013) and in decisions that tap upon learned values. Finding that in our learning task the immediate context does not exert any influence on choices does not automatically overrule previous distractor effects obtained in single-shot tasks. It rather suggests that in value-learning tasks, where choices are guided by past rewards, the relative influence of the immediate context dissipates. This null immediate context effect could be partially ascribed to the presence of only three alternatives in each mini-block. Due to the relatively low demand of maintaining three items in memory, context-dependent value computations could have consistently relied on the entire set of alternatives, even in binary trials. Value-learning tasks involving several alternatives could perhaps reveal a more complex interplay between the influence of the temporal and the immediate context.

Although the design of our study closely followed the design in Louie et al. (Louie et al., 2013), we failed to replicate the strong negative distractor effect they found in the choice behavior of two monkeys. The negative distractor effect in Louie et al. was described as an immediate context effect attributed to divisive normalization. However, recent research from our lab (Cao & Tsetsos, 2023) has shown that a negative distractor effect can emerge without the recruitment of normalization mechanisms. This can occur when learning is conducted through choices among two or more alternatives, with reward feedback delivered exclusively for the chosen alternative. In these cases, in a high-distractor context, the distractor alternative is chosen (sampled) more frequently compared to a low-distractor context. As a consequence, participants in the high-distractor context sample the two high-value alternatives less often, exhibiting a lower choice accuracy due to increased value uncertainty (i.e., an “emergent” negative distractor effect). While in Louie et al. single-item learning trials preceded the choice phase, it is conceivable that the two monkeys continued to learn the values of the alternatives from the partial feedback received in the choice phase. This could have led to an “emergent” negative distractor effect owing to compromised learning in the high-distractor context (Cao & Tsetsos, 2023). By contrast, in our task, learning seemed to occur primarily during the learning phase and ceased in the choice phase. This was substantiated by the lack of differences in behavior between “Feedback” and “No-Feedback” mini-blocks, suggesting no further learning during the “Feedback” choice trials. The rapidly stabilized learning in our task prevents an “emergent” effect from arising. Thus, the discrepancy between our findings and those in Louie et al. (Louie et al., 2013) can be reconciled if the negative distractor effect was “emergent” in their case. Taken together, the possibility that the negative distractor effect can emerge due to learning dynamics, challenges the view that divisive normalization is a generalized mechanism extending from low-level sensory representations (Heeger, 1992; Normann & Perlman, 1979; Olsen et al., 2010; Rabinowitz et al., 2011; Reynaud et al., 2012) all the way up to value-based decisions (Louie et al., 2013; Soltani et al., 2012; Webb et al., 2020, 2021).

A central finding in our study was that value estimates and choices did not align with either classic positive or negative distractor effects. Instead, we observed considerable individual variability, with different participants exhibiting either positive or negative effects. Individual variability has also been recently reported in multi-attribute context effects (Spektor et al., 2021; J. S. Trueblood et al., 2015), overturning a long-held assertion about the directional nature of certain context effects. Thus, our findings, together with those from the multi-attribute literature, begin to paint a richer empirical landscape. Future work could shift away from theoretical frameworks making rigid, one-directional predictions and instead focus on understanding the neural and computational mechanism that give rise to variability in context-dependent valuation. Across these lines, inspired by the decision-by-sampling and “frequency” models (Hayes & Wedell, 2023b; Noguchi & Stewart, 2018a; Stewart et al., 2006), we developed a stochastic rank-based model that encompasses both positive and negative distractor effects while predicting a robust value reduction in high-distractor contexts, similar to the behavioral data.

To conclude, our findings suggest that during value-learning, the value of an inferior (distractor) alternative distorts value representations over a long timescale spanning several learning and choice trials. Crucially, the direction of this distortion is subject to across-participants variability, which divisive and range normalization theories cannot capture. Instead, this variability is best captured by a mechanism that constructs subjective value representations via comparing the value of the target alternative with the value of other alternatives, sampled from the memory context. These findings shed new light on the mechanisms that govern value learning and decision-making among multiple alternatives.

Materials and Methods

Participants

Experiment 1, onsite: We recruited 30 participants (22 women, M = 25.3 years, SD = 3.41) from the internal participant pool in the Institute of Neurophysiology and Pathophysiology of the University Medical Center Hamburg-Eppendorf. This sample size had 56% power to capture the Cohen's d = 0.4 corresponding to a small to medium effect size with $\alpha = 0.05$ using a two-sided t-test.

Before starting the experiment, all participants gave written informed consent. The study was approved by the local ethics committee of the Hamburg Medical Association. All participants had normal or corrected-to-normal vision were right-handed, with the exception of one participant who was left-handed. The experimental session lasted between 3 and 3.5 hrs. Participants received €30-35 for their participation (hourly net rate = €10). In addition, we included a €10 completion bonus and a maximum of €15 task performance bonus to further incentivize participants to accurately perform the task. The average final task performance bonus was €13.76 (95% CI = [€13.63, €13.90]), which was significantly higher than what would have been expected if participants chose randomly ($t_{(29)} = 41.3$, $p < 0.001$).

Experiment 2, online: Sixty-eight (28 self-reported women, 38 self-reported men and 2 undisclosed, M = 30.5 years, SD = 5.5) participants were recruited via prolific (*Prolific*, 2014) and completed the experiment in two sessions (each approximately 45 minutes) within one week. This sample size provided us with the power of 90% to capture the effect size of d = 0.4 with $\alpha = 0.05$ using a two-sided t-test.

Before starting the experiment, all participants gave written informed consent. The study was approved by the School of Psychological Science Research Ethics Committee at the University of Bristol (approval code: 10270). All participants reported that they have normal or corrected-to-normal vision; and 59 of them were right-handed. Participants received £18 for their participation (hourly net rate = £12). In addition, we included a £2 completion bonus and a maximum of £3 task performance bonus to further incentivize participants to accurately perform the task. The average final task performance bonus was £2.39 (95% CI = [£2.35, £2.43]), which was significantly higher than what would have been expected if participants chose randomly ($t_{(67)}$ = 20.06, $p <$ 0.001).

Procedure

Experiment 1, onsite: The task was implemented using Psychophysics Toolbox, psychtoolbox-3 (Brainard, 1997; Kleiner et al., 2007), and presented on a 21” monitor (1920 x 1080 px screen resolution and 120-Hz refresh rate). Participants viewed the monitor in a dimly lit room from a 60 cm distance.

Experiment 2, online: We used the Gorilla Experiment Builder (*Gorilla Experiment Builder*, n.d.) to create and host our experiment. Participants were recruited through Prolific (*Prolific*, 2014).

In both experiments, participants were instructed to complete 48 mini-blocks of a value learning task (Figure 2A). Their task was to collect valuable-colored coins to maximize their overall obtained reward. Each mini-block started with a learning phase where participants learned the association between colored coins and reward-values (Figure 2B). Later, they faced binary and ternary choices in the choice phase, aiming to choose the alternative (colored coins) with the highest reward (Figure 2D). Following the learning and choice phases we added two estimation phases, in which participants reported their subjective value estimates for each colored coin (Figure 2C). In each mini-block, the value of all three alternatives (i.e., the context) was kept fixed. We randomly assigned the three alternatives, the higher-value (HV), lower-value (LV), and distractor value (DV), to three colored circles (red, blue, and yellow); this maps them onto three imaginary coins of different values which are specific to each mini-block. In total, we created four unique contexts by deploying two levels of distractor value, DV = {18, 40}, allowing us to assess the distractor effect, and two magnitude levels for high-value alternatives to insert variability into the task, HV = {55, 50}, LV = HV – 5. The magnitude level (HV equal to 55 or 50) did not yield any significant effects in any of the key analyses.

Therefore, for the sake of simplicity, we collapsed the data across the two magnitude levels. Combining these four contexts with a full color-reward permutation, led to 24 unique possible mini-blocks (six color-reward permutations times four unique value contexts). These mini-blocks were repeated twice, in a total of 48 mini-blocks. In half of the mini-blocks, we did not provide any reward feedback in the choice phase ("No-Feedback" mini-blocks) while in the other half we showed the reward associated with each choice ("Feedback" mini-blocks). We instructed participants that "Feedback" and "No-Feedback" mini-blocks were randomly interleaved and that there was no way to know which mini-block they were performing prior to the choice phase. This ensured that the participants paid attention to the learning phase equally in "Feedback" and "No-Feedback" mini-blocks, enabling us to attribute any behavioral disparities across the two conditions to the choice phase. In Experiment 1, all participants received verbal instructions about the task structure, and commenced the main experiment after completing two practice mini-blocks. In Experiment 2, however, we were unable to provide verbal instructions; instead, we provided participants with detailed written instructions before starting the experiment followed by six comprehension questions. We only allowed the participants who correctly answered all six comprehension questions about the instructions to participate in the experiment.

Stimuli

***Alternatives*:** The stimuli were three colored filled circles (diameter size = 1.5 visual degrees according to Experiment 1). The colors were yellow = [255 250 100], red = [255 90 90], and blue = [100 153 255]. Stimuli were presented on a grey background, [127.5 127.5 127.5].

***Reward*:** The presented reward was a set of moving dots (diameter dot = 0.15 visual degrees) framed in a circle (frame thickness = 0.075 visual degrees, frame color = [51 51 51]). The number of dots was equal to the associated value of the chosen alternative (see the value sets mentioned in the main task section). The color of each dot was grayscale ([127.5 127.5 127.5]) and its contrast was drawn from a uniform distribution: [0.6 1]. The reward presentation duration in both learning and "Feedback" choice trials was 0.75 seconds. We presented the dots in 10 consecutive frames (frame duration = 75 ms) and induced motion by randomly assigning each dot to a new location in each frame. To make the human reward feedback as similar as possible to the monkeys' juice delivery in the original study (Louie et al., 2013), we needed to introduce some degree of "internal" uncertainty into the reward perception. Thus, instead of showing the dots statically on the screen, we presented them in a dynamically moving format, to induce uncertainty at the perceptual level.

Mini-block structure

Learning phase: Participants completed 9 randomly presented learning trials (three per each alternative). Each trial started with the presentation of a fixation cue for a random short time (randomly drawn from a truncated exponential distribution: [0.5 1] and mean = 0.75 (seconds)). Then the stimulus, one colored coin, was presented at the center of the screen for a maximum of 2 seconds. Participants were asked to learn the value of the stimulus within 2 seconds and collect (by clicking on that in Experiment 1 and pressing the "SPACE" bar in Experiment 2) its associated reward. If they failed to do so, they missed the reward and saw a "Missed response" message on the screen; in Experiment 1, once the stimulus appeared on the screen the mouse pointer appeared on a random position of an imaginary circle whose center aligned with the stimulus (diameter = 2 visual degrees). Immediately after their response, participants could see a centrally presented cloud of moving representing the reward associated with the stimulus. The reward was presented for 0.75 seconds and then followed by a gray screen with the fixation point on the center as inter-trial-interval (ITI) (Experiment 1: ITI = 1.25 seconds, and Experiment 2: ITI = 0.25 seconds).

Estimation phase: We had 3 estimation trials, one for each alternative, presented in random order. In each estimation trial, we presented a target alternative (shown at the bottom-center of the bar) and asked participants to report the estimated value of the alternative corresponded to. They did so by first moving a slider on a bar within 10 seconds to find the best estimation and then pressing the "SPACE" bar to confirm their estimation. After 10 seconds, the current trial was automatically terminated and the next estimation trial was initiated. At the top of the two ends of the bar, we statically displayed the minimum (15 dots) and maximum (85 dots) possible number of dots, which we encouraged participants to use as reference. As participants adjusted the slider, they could instantly observe the number of moving dots within a set displayed at the top center in Experiment 1 and as a numerical value in Experiment 2, both changing in real-time.

Choice Phase: The choice phase included 12 ternary and 12 binary choice trials which were presented in random order. We had 3 combinations of binary trials {(HV, LV), (HV, DV), (LV, DV)} and presented each 4 times. The mapping between the location of the alternatives, (left, top, right) in ternary trials and (left, right) in binary trials, and the alternatives was counterbalanced. As in the learning trials, each trial began with the presentation of a fixation cue for a short delay (randomly drawn from a truncated exponential distribution: [0.5 1] and mean = 0.75 sec). Then the stimuli appeared on the screen for a maximum of 2 seconds. The stimuli were equidistant from the center (eccentricity = 2 visual degrees). Participants were asked to report (by clicking on that in Experiment 1 and pressing the associated arrow key in Experiment 2) their preferred stimulus within 2 seconds to collect the associated reward for their choice. Failure to respond within the deadline resulted in a “Missed response” message appearing on the screen; in Experiment 1, on each choice trial the mouse pointer was initiated at the center of the screen. In “Feedback” mini-blocks, the reward was presented at the center of the screen immediately after a choice was made. The reward stayed on the screen for 0.75 seconds, followed by ITI (Experiment 1: ITI = 1.25 seconds, and Experiment 2: ITI = 0.25 seconds). In “No-Feedback” mini-blocks a choice was directly followed by the ITI window.

Bonus window: We presented a bonus window twice, at the end of each estimation phase. In Experiment 1, this window illustrated the cumulative bonus earned from the start of the task until that moment, represented by a pink bar whose length visually reflected the accumulated bonus. A cyan line indicated the maximum possible bonus attainable. Consequently, the space between the end of the pink bar and the cyan represented the bonus participants had missed. In Experiment 2, we used two different bars, one showing the collected reward so far in green and the other one presenting the missed reward in red. The length of each bar indicated the maximum bonus they could either achieve or miss in the experiment.

Behavioral Analyses

Across different analyses, we used one-sample *t*-tests, ANOVA, and Pearson correlation. In the correlation analyses, we first obtained a correlation coefficient for each participant and then compared the correlation coefficients of the group against zero. All analyses were done using Matlab (The MathWorks Inc., 2022). For the interpretation of null effects, we used JASP (JASP Team, 2023) and its default setting to calculate the corresponding Bayes factor (BF_{01}) in favour of the null hypothesis.

Relative choice**:** To quantify the distractor effect we compared the relative choice in the choice phase between the two contexts with the high-value and low-value distractors. The relative choice quantifies the choice share of the two high-value alternatives relative to each other:

$$p(HV\ over\ LV) = \frac{p(HV)}{p(HV) + p(LV)}, \qquad (1)$$

where *p(HV)* and *p(LV)* indicate the choice probability of the high-value and low-value alternatives.

The distractor effect is quantified as:

$$DE = p(HV\ over\ LV|high\_D) - \ p(HV\ over\ LV|low_D) \qquad (2)$$

Thus, *DE > 0*, *DE < 0*, and, *DE = 0*, indicate a positive, a negative, and a null distractor effect respectively.

We only analyzed trials in which participants responded within the 2-second deadline in the learning and choice phases and the 10-second deadline in estimation phases, that is 99.9±0.03% of the learning trials, 99.7±0.1% of the estimation trials, and 99.7±0.06% of the choice trials. Here and in the text, we reported the mean with standard error-of-mean (SEM) across participants. Depending on the appropriate test for each analysis, the statistical effects were examined using one-sample *t*-tests, *F*-test using ANOVA, and Pearson correlation. In the correlation analyses, we first ran the correlation on each participant and to test for effects at the group level we then ran a two-sided *t*-test on the correlation coefficients against zero. All analyses were done using MATLAB (The MathWorks Inc., 2022) and we used JASP (JASP Team, 2023) to do Bayesian *t*-tests.

***Choice prediction using subjective values*:** To convert the estimated values into pseudo-choices, we applied an *argmax* selection rule (like the one used here (Bavard & Palminteri, 2023)) on each ternary trial as:

$$p(a) = \begin{cases} 1 & if \quad SV(a) > SV(b)\ and\ SV(a) > SV(c) \\ 0.5 & if \quad SV(a) > SV(b)\ and\ SV(a) = SV(c) \\ 0.3 & if \quad SV(a) = SV(b) = SV(c)' \\ 0 & if \quad SV(a) < SV(b)\ or\ SV(a) < SV(c) \end{cases} \tag{3}$$

and on each binary trial as:

$$p(a) = \begin{cases} 1 & if \quad SV(a) > SV(b) \\ 0.5 & if \quad SV(a) = SV(b), \\ 0 & if \quad SV(a) < SV(b) \end{cases} \tag{4}$$

where *SV(x)* is the value estimate for alternative *x* and *p(x)* is the predicted choice probability of that alternative in each trial.

Computational Models

To model the choice behavior objective values (OV_i) were transformed into "subjective" values (SV_i), with the transformation type differing across models. Transformed values (SV_i) were converted to choice probabilities by applying a probit function (using a numerical approach, Equation 5). For each alternative *i* the choice probability *p(i)* was calculated as:

$$p(i) = \int_{-\infty}^{\infty} \left(f(x; SV_i, \sigma_f) \cdot \prod_{j \neq i}^{n-1} F(x; SV_j, \sigma_f) \right) dx, \tag{5}$$

where *f* indicates the probability density function and *F* is the cumulative distribution function. Here we assumed that all represented subjective values are normally distributed (*N*(SV, σ^2_f)) and *n* is the number of alternatives. We used this range: [eps 100] for σ^2_f to fit the model.

We used four computational models with each describing an alternative mechanism mapping objective values into their subjective (transformed) counterparts.

Probit model (Pr): This model assumes that the subjective values should be unaffected by the choice-set context. Thus, there is no transformation in this model and the subjective values are encoded as equal to the objective values.

$$SV_i = OV_i \tag{6}$$

Divisive normalization model (DN): The subjective value of each alternative is normalized by the sum of all alternatives.

$$SV_i = k * \frac{OV_i}{\sigma + w * \sum_{n=1}^{3} OV_n}, \tag{7}$$

where k, σ, and w are gain, semi-saturation, and weight terms. To fit the model we constrained parameters in these ranges, respectively: [1 200], [1 200], and [0 1].

Range normalization model (RN): The subjective value of each alternative is normalized by the range of values in a given context.

$$SV_i = \frac{OV_i}{1 + w * (\max(OV's) - \min(OV's))}, \tag{8}$$

where *OV's* refers to a vector consisting of all alternative values in the context and *w* is a weight term. To fit the model we constrained *w* between [0 1].

Rank-based model (RB): This model implements relative value coding using a series of memory-based binary comparisons across all possible pairs of alternatives in the context. The subjective value of each alternative is the total number of times that this alternative was the winner across all memory-based binary comparisons.

$$SV_i = k_{ij} * \sum_{j \neq i}^{n-1} p_{(i>j)}, \tag{9}$$

where k_{ij} represents the total number of binary comparisons, constrained in the [1 200] range. $p_{(i>j)}$ is the probability that alternative *i* is deemed as better than alternative *j* in a given binary comparison. We derived this probability using a softmax function:

$$p_{(i>j)} = \frac{\exp\left(\frac{OV_i}{\tau}\right)}{\exp\left(\frac{OV_i}{\tau}\right) + \exp\left(\frac{OV_j}{\tau}\right)}, \tag{10}$$

where τ is the temperature parameter, which was constrained in the [1 100] range when fitting the model.

Model simulations: The model predictions shown in Figure 1 were generated using numerical approximations (see Equation S3). In all models, we used the same value sets: HV = 50, LV = 45, and DV = {0, 7, 13, 20, 27, 33, 40}. The parameters for each model were fixed as follows: Pr: σ^2_f = 30.25, DN: σ^2_f = 9, k = 100, σ = 50 and w = 1, and RN: σ^2_f = 0.25, and w = 1. In Figure 5D and 5E the parameters to simulate the RB model in equal binary comparison were: σ^2_f = 36, τ = 20, k_{HVvsLV} = k_{HVvsDV} = k_{LVvsDV} = 40, and in unequal binary comparison were: σ^2_f = 400, τ = 20, k_{HVvsLV} = 60, k_{HVvsDV} = 40, k_{LVvsDV} = 20. In Figure 5F, we used the same value sets as Figure 5D and 5E: HV = 50, LV = 45, but only two levels of distractors DV = {18, 40} to be able to calculate the distractor effect (Equation 2) and the parameters were: σ^2_f = 100, τ = 20, k_{HVvsLV} = 20 to 60, k_{HVvsDV} = 20 to 60, k_{LVvsDV} = 20 to 60.

Model fitting procedure: We fitted the models by minimizing the negative log-likelihood (*NLL*) summed over all choice trials (including all ternary and binary trials) (Wilson & Collins, 2019). For each participant, we fitted each model once on the entire set of choice trials, including both "Feedback" and "No-Feedback" mini-blocks (~1152 choice trials). We optimized the parameters using Matlab's *fmincon.m* function (MaxFunEvals = 5000; MaxIter = 5000; TolFun = 1e-20; TolX = 1e-20). To avoid local optima, we refitted each model for each participant 10 times using a grid of randomly generated starting values for the free parameters.

Model selection: We used a fixed-effects and a random-effects model comparison. We used the Bayesian information criterion (*BIC*) to compare different models. The *BIC* is quantified as below:

$$BIC = k * \ln(n) - 2 * \ln(L) \tag{11}$$

where *L* is the likelihood value obtained from the model fit to all choice data, *k* is the number of free parameters in each model and *n* is the number of trials we used to fit the model (Schwarz, 1978). We computed the *BIC* score for each participant and each model. Then for each participant the model with the lowest *BIC* was marked as the best-individualized model. Finally, we reported the *ΔBIC* of each model relative to the best-individualized model (Figure 6B).

We also fitted the models using a 6-fold cross-validation procedure. To do so, for each participant, we split the trials into 6 parts (i.e., folds) and then fitted each model to a "training" set (comprising five random folds). We used the best-fitted parameters of the "training" set to calculate the *LL* summed across trials in the left-out "test" fold. We repeated this process over test folds (6 times) and the final cross-validated *LL* was computed as the mean *LL* across cross-validated folds. We then used this mean *LL* to calculate each model's posterior frequency and protected exceedance probability (i.e., the probability corrected for the chance level that a model is more likely than any others) using the variational Bayesian analysis (VBA) toolbox (Daunizeau et al., 2014; Rigoux et al., 2014).

Acknowledgments

This work was supported by the EU Horizon 2020 Research and Innovation Program (ERC starting grant no. 802905) to Konstantinos Tsetsos.

Extended Data

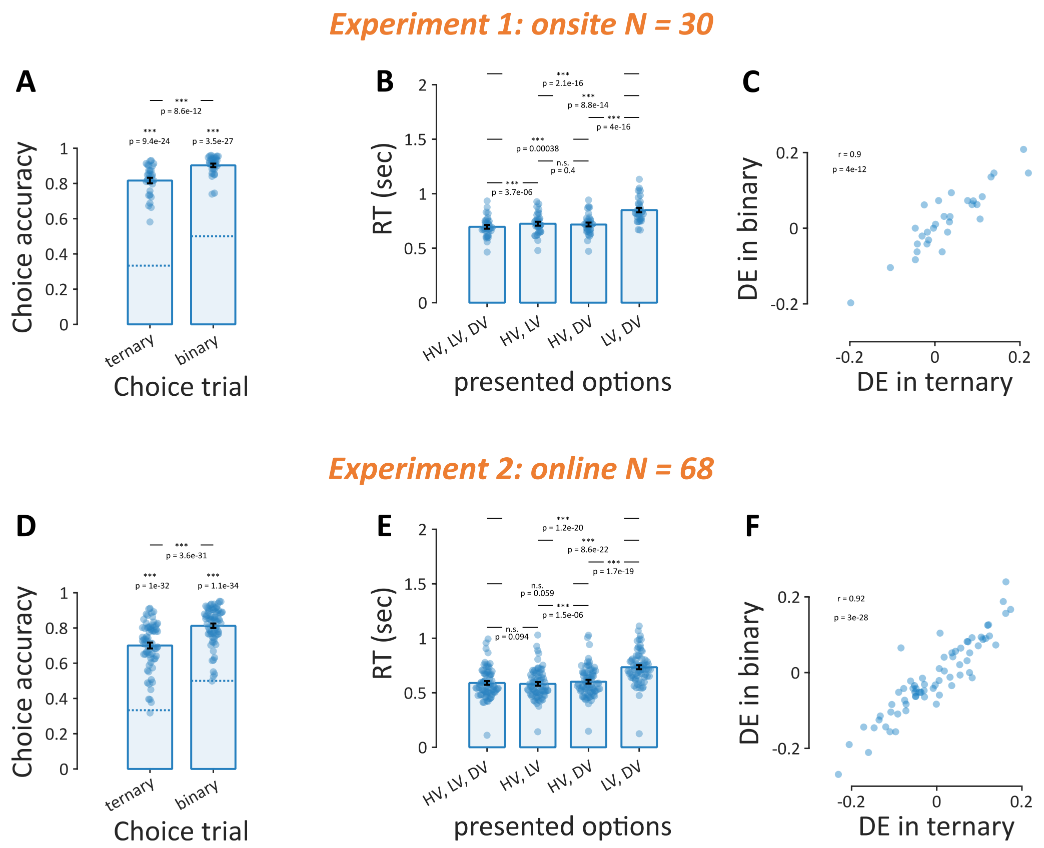

Figure S1. Complementary behavioral data from each experiment. (A, D) Choice accuracy of ternary and binary trials pooled across both "Feedback" and "No-Feedback" were significantly higher than chance. **(B, E)** The reaction time of participants' choices (both correct and incorrect choices) illustrated for each trial type. The RT in ternary trials is significantly lower than any binary trials. Within binary trial types, "LV, DV" pair has the significant higher RT than the other two binary pairs. **(C, F)** The correlation between the distractor effect in ternary and binary trials. The error bars are standard errors of the mean across participants and the dots indicate individual participants.

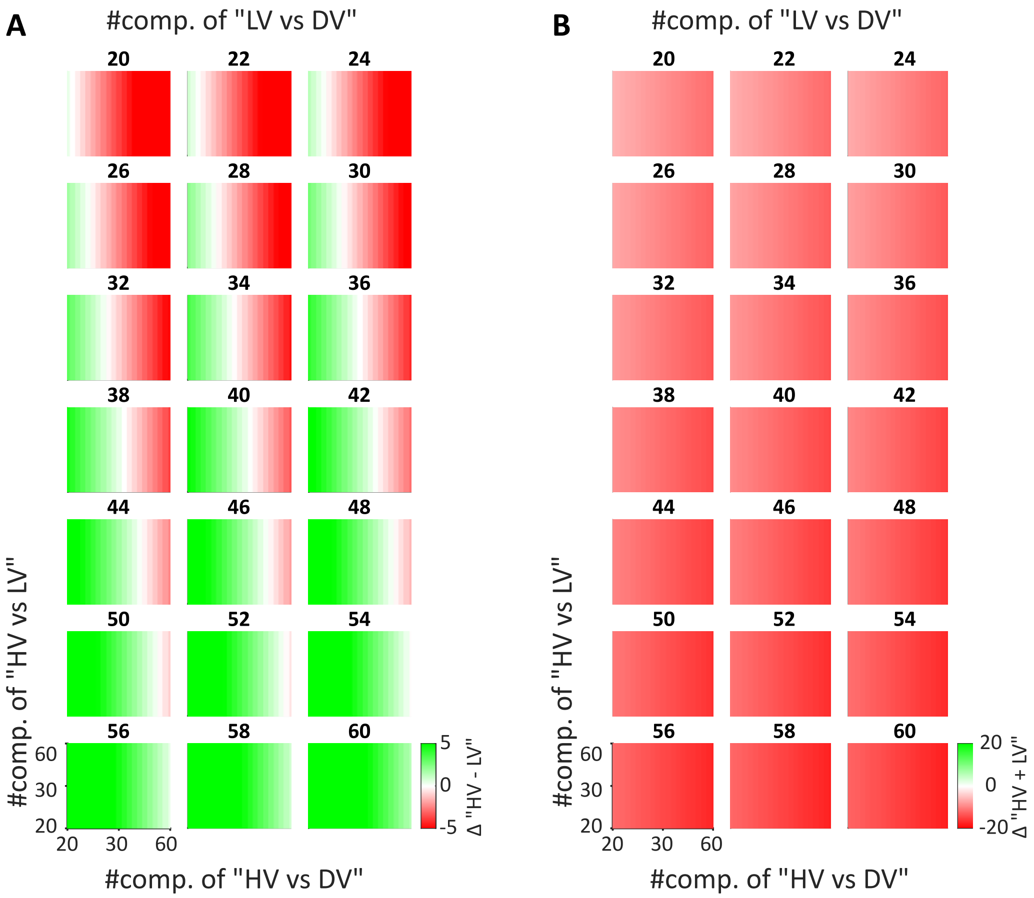

Figure S2. RB model simulation. (A) Delta of *"HV - LV"* as the function of the number of binary comparisons. **(B)** Delta of *"HV + LV"* as the function of the number of binary comparisons.

Table S1. Best-fitted model parameters, (mean ± standard error of the mean across participants, aggregated across both experiments, N = 98).

Model / **Parameter**	RB	Pr	DN	RN
k	-	-	92.34 ± 5.08	-
$\mathbf{k_{HVvsLV}}$	42.78 ± 3.45	-	-	-
$\mathbf{k_{HVvsDV}}$	41.66 ± 4.06	-	-	-
$\mathbf{k_{LVvsDV}}$	33.32 ± 4.20	-	-	-
τ	54.48 ± 4.13	-	-	-
σ	-	-	87.59 ± 5.78	-
w	-	-	0.18 ± 0.04	0.28 ± 0.04
$\boldsymbol{\sigma^2_f}$	79.77 ± 2.18	60.67 ± 3.66	55.72 ± 2.59	20.64 ± 3.15

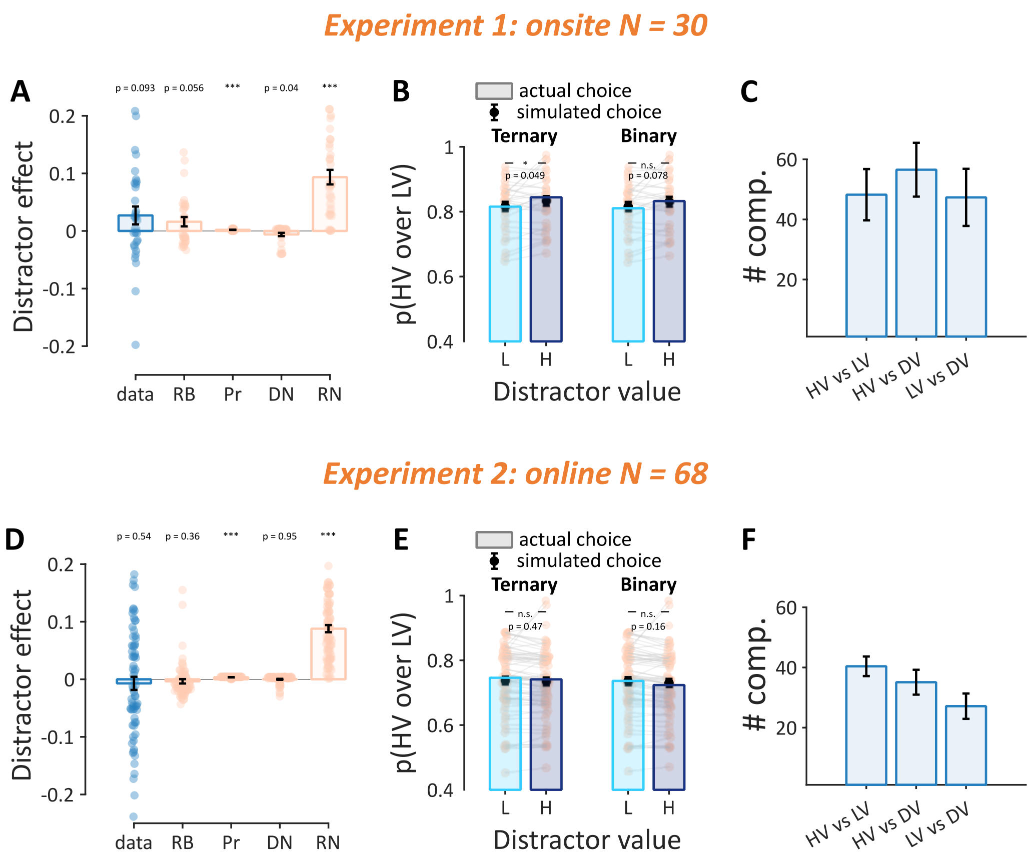

Figure S3. Model predictions. (A, D) Distractor effect comparison between the actual data and simulated data using the best-fitted parameters. **(B, E)** The simulated relative choice of the RB superimposed on the actual relative choice. **(C, F)** The distribution of fitted *k* parameters in each experiment (1-way ANOVA in Experiment 1: $F(2, 87) = 0.32$, $p = 0.73$; and Experiment 2: $F(2, 201) = 2.94$, $p = 0.06$). In all panels, the error bars are standard errors of the mean across participants, and the colored dots indicate the individual participant calculated using the best-fitted parameters of each model.

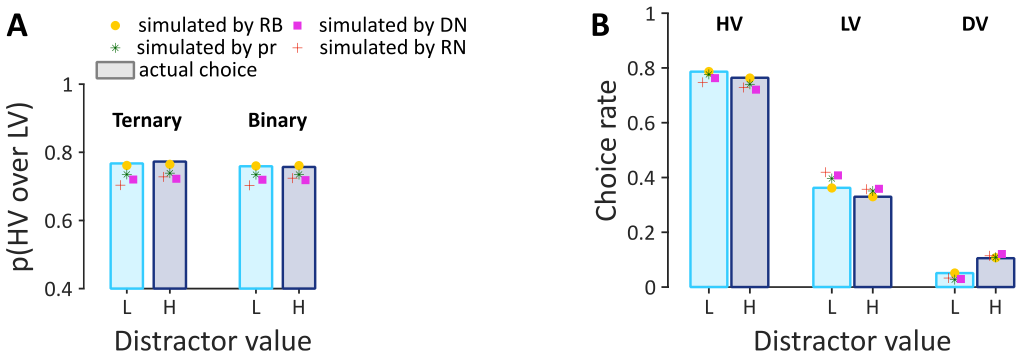

Figure S4. Model predictions. (A) The simulated relative probability of HV over LV, and **(B)** The simulated choice rate of each model superimposed on the actual data. In all panels, the simulated data points were calculated using the best-fitted parameters of each model, and the error bars are standard errors of the mean across participants.

3 | Immediate context-dependence in multi-alternative perceptual decisions

Summary

Decisions are rarely made in isolation; they are often influenced by either spatial or temporal features of the context. Several studies have shown that the choice between two economic alternatives can be influenced by the introduction of a third, inferior alternative (referred to as a distractor), contrary to the principles of rational choice theory. However, it remains unclear whether the presence of a distractor enhances (i.e., positive distractor effect) or impairs (i.e., negative distractor effect) choice accuracy, or whether it modulates reaction time with no discernible choice effect. To better understand these conflicting effects, we designed a perceptual choice task. Using perceptual alternatives instead of economic values allowed us to objectively map a single perceptual stimulus to a decision value. This allowed us to eliminate the impact of the time course of value learning on value representation and thoroughly investigate the influence of the immediate context on decision-making. Most importantly, we sought to determine whether the distractor effect reported in value-based decisions generalizes to perceptual decisions. Our results indicate that a higher-value distractor alternative prolongs the decision process, but does not affect choice accuracy. Existing static context-dependent models cannot intrinsically explain the distractor effect on reaction times. To address this gap, we propose a dynamic model that includes valuation and decision stages. During the valuation stage, the model uses a combination of normalization and memory-based binary comparison to calculate subjective values. The decision-making process is followed by feeding the subjective values to a race model that ultimately determines choice and reaction time.

Introduction

Understanding how people choose their preferred alternative has been a central focus in cognitive science, with a recent surge of interest in multi-alternative conditions (Berkowitsch et al., 2014; Chau et al., 2014; Chung et al., 2017; Cohen et al., 2017; Evangelidis et al., 2024; Hunt et al., 2014; Landry & Webb, 2021; Louie et al., 2013; Mohr et al., 2017; Spektor et al., 2021). Rational choice theories state that the best alternative should be always chosen, regardless of the number and value of other alternatives in the choice set (Luce, 1959, 1977). However, experimental results have shown a violation of the independence from irrelevant alternatives (IIA) principle, a class of phenomena known as context effects (Dumbalska et al., 2020; Evangelidis et al., 2024; Spektor et al., 2021; Stanley & Wedell, 2024, 2024; Tsetsos, Chater, et al., 2012; Tsetsos et al., 2010).

Various forms of context effects have been reported mainly in complex multi-attribute decisions (Evangelidis et al., 2024). However, recent research has uncovered a novel context effect in simpler single-attribute decisions (Chau et al., 2014; Itthipuripat et al., 2015; Louie et al., 2013). The so-called "distractor effect" occurs when the introduction of a less desirable alternative (i.e., distractor) into the choice set influences preferences among other high-value alternatives. The direction of the distractor effect on choice has been a matter of debate. In 2013, Louie et al first documented that there is a negative correlation between the value of the distractor alternative and the choice share (see Equation 1) of the best and second-best alternatives (Louie et al., 2013). This so-called negative distractor effect states that a higher distractor alternative leads to a lower choice share of the best alternative. In line with previous neural findings supporting relative neural coding due to normalization processes (Louie et al., 2011), they proposed that divisive normalization is a general mechanism underlying context-dependent decision-making (Louie et al., 2013). Subsequent studies have undermined this conclusion and the decision-theoretic relevance of divisive normalization theory. For example, a consistent pattern of both positive and negative distractor effects has been reported in several studies of reward-learning decision-making tasks (Chau et al., 2020). In addition, replications of the original study by Louie et al. showed a null distractor effect in agreement with IIA. Instead, these studies reported slower decisions in the presence of a high-value distractor alternative (Gluth et al., 2020; Itthipuripat et al., 2019).

Taken together, the empirical evidence has shown that there is no definitive conclusion about the direction of the distractor effect on choice. As a result, the mechanisms by which the value of a third alternative influences decisions remain unclear. First studies have investigated the influence of the distractor on the choice using value-learning tasks (Bavard & Palminteri, 2023; Itthipuripat et al., 2015, 2019), in which decision-making occurred either during or after a learning phase. Thus, these studies were not well-suited to disentangle the effects of immediate context from those of temporal context on choice. A recent study showed that asymmetric sampling in value learning tasks produced the distractor effect (Cao & Tsetsos, 2023). In addition, in our previous research, we showed that value distortion and the subsequent context effect emerge over time in a value learning paradigm (Tohidi-Moghaddam & Tsetsos, 2025). Thus, to examine the distractor effect on choice a simpler design is needed in which value information is not learned over time but can be constructed at the choice moment.

Here, we investigated the influence of a distractor alternative using a perceptual task. Our first goal was to carefully control for the availability of all value information on a single trial basis, guaranteeing no effect of the previously learned value on the current value representation and the subsequent choice. This would give us a clear understanding of the distractor effect in the decision-making process in an immediate context. Second, the strong evidence for normalization theories in perception motivated the idea of the canonical computational mechanism of normalization in economic decisions (Carandini & Heeger, 1994, 2011; Heeger, 1992; Normann & Perlman, 1979; Olsen et al., 2010; Reynolds & Heeger, 2009). Thus, a perceptual task in which contrast level is associated with the value of each alternative would be well-suited to test the account of normalization theory in context-dependent decision-making. More importantly, the purpose of this study was to examine the robustness of any observed distractor effect in the simpler perceptual decision task. It has been previously shown that the context effects in multi-attribute decisions are not limited to economic decisions (J. S. Trueblood et al., 2013; Tsetsos, Chater, et al., 2012). Recently, studying the decision-making process using simple perceptual stimuli has become popular because it allows developing data-driven computational theories (Brown & Heathcote, 2008; Gold & Shadlen, 2007; Shadlen & Newsome, 2001b; Usher & McClelland, 2001). Consequently, our investigation sought to shed light on the generalizability of these effects and the underlying computational mechanisms.

Here, data from two different perceptual tasks support the absence of a distractor effect on choice, while indicating a delay in the decision-making process when a higher distractor alternative is present in the choice set, which we refer to as the negative distractor effect on response time (RT) (Gluth et al., 2020; Itthipuripat et al., 2019). Based on existing evidence in perceptual neuroscience (Carandini & Heeger, 2011; Reynolds & Heeger, 2009), we postulated that this negative RT effect could be attributed to greater suppression of values in a high-distractor context. Assuming that a diffusion process is involved in reaching the motor action boundary, the increased suppression results in a longer time to reach the boundary. Thus, we proposed a theoretical framework consisting of valuation and action stages. The valuation stage is elucidated by the interaction between low-level normalization and high-level, memory-based, binary comparisons. Both normalization and binary comparison mechanisms suppress the value representation. Normalization reduces the difference between the value of the two best alternatives when the distractor value is high, while the latter increases it. These high and low value differences result in negative and positive distractor effects, respectively. In this framework, these two effects cancel each other out, resulting in no effect on choice. In the action stage, a single racer completes the decision process by selecting the winning alternative. The suppressed value that passes into the race model can explain the distractor effect on reaction time (RT). We further explored the role of arousal in the distractor effect on choice and reaction time (RT). We did not observe any modulation of arousal on the distractor effect on reaction time (RT). Interestingly, however, we found that the distractor effect on choice changed from negative to positive as arousal increased. This observation provides further support for our proposed model. Overall, these findings aim to improve the theoretical and practical understanding of the effects of the immediate context on multi-alternative decision-making processes.

Results

Task description and basic performance

***3AFC perceptual task, GB*:** Thirty-two participants engaged in a three-alternative forced-choice (3AFC) perceptual task involving the selection of the highest contrast among three Gaussian Blobs with distinct contrasts (Figure 1A). Before the main experiment, each participant completed a two-forced alternative discrimination perceptual task to determine their individualized just noticeable difference (JND). Utilizing this JND, we established five contrast levels: 0.5 + [-2JND, -JND, 0, +JND, +2JND]. Then, choosing three contrast levels from these five without replacement generated 10 trial conditions (Figure 1B). To investigate the distractor effect, we focused on six conditions meeting specific criteria for distractor effect analysis (e.g., in Figure 1B, 4, 6, and 8 are defined as low distractor conditions, and 5, 7, and 9 are marked as the corresponding high distractor conditions, respectively). Each of the ten conditions was repeated 12 times per block, resulting in 120 trials. Participants were required to maintain fixation throughout each trial. So, each trial was initiated with a fixation cue and remained on the screen during the whole trial. Following a brief random presentation of the fixation cue solely, three stimuli equidistant from the fixation cue appeared on the screen for either 0.5 or 1.5 seconds, randomly assigned and counterbalanced (labeled as “short” and “long” trials in the text). After the stimulus offset, the rotation of the fixation cued the response window, during which participants had one second to report their decision to receive appropriate feedback. Furthermore, we manipulated the distance of stimuli from the fixation cue in alternating blocks throughout the experiment (denoted as "Near" and "Far" blocks in the text). Participants completed 99.6$\pm$6e-4% of the trials with an average response time of 386.7$\pm$15.1 milliseconds (ms), the reported response time is the sum of 150 (ms) after the stimulus offset plus participants’ reaction time during the response window. Figure 1D shows that participants chose the best alternative (i.e., the alternative with the highest contrast in each trial) with 78.8$\pm$0.01% accuracy in all trials (chance level 33.3%; one-sided t-test against chance level $t(31)$ = 41.34, p < 0.001). The choice accuracy was significantly higher in “long” than the “short” trials and it was higher in “near” than the “far” trials. (two-way ANOVA on the choice probability of the best alternative: stimulus duration: $F(1,127)$ = 6.27, p < 0.01, eccentricity: $F(1,127) = 27.3$, $p < 0.001$, interaction: $F(1,127) = 0$, $p = 0.98$, see Figure S1 in the Extended Data). Expectedly, the reaction time was only influenced by the stimulus duration and it was significantly higher in the "short" trials rather than the "long" trials. (2-way ANOVA on the *log*(RT): stimulus duration: $F(1,127) = 11.4$, $p < 0.001$, eccentricity: $F(1,127) = 0.06$, $p = 0.81$, interaction: $F(1,127) = 0.02$, $p = 0.89$, see Figure S1 in the Extended Data).

***3AFC perceptual task, Gabor*:** Twenty participants performed a three-alternative forced-choice (3AFC) perceptual task similar to the "GB" experiment, albeit with a few differences. The stimuli were perceptual "Gabor" patches with varying contrast levels, the adjustment of contrasts and the trial conditions were identical to the "GB" task (Figure 1B). Like the "GB" experiment, each trial began with a fixation cue, persisting throughout the trial. Subsequently, three stimuli equidistant from the fixation cue (analogous to the "far" blocks in the "GB" experiment), appeared on the screen. After 1 second, a framing cue, ("Low" or "Hig") indicating the response target contrast, replaced the fixation cue for 0.3 seconds. Then the fixation cue was replaced back and the stimuli were still on the screen for an additional 2.5 seconds. At 0.15 seconds after the stimulus offset, the rotation of the fixation cue indicated the beginning of the response window where participants reported their decisions within a maximum of 2 seconds to receive appropriate feedback. Participants successfully completed $99.6\pm0.001\%$ of the trials with an average response time of 658.6 ± 37.5 milliseconds (ms). The reported response time encompasses the sum of 150 (ms) after the stimulus offset plus participants' reaction time during the response window. Figure 1E shows that participants chose the best alternative (i.e., the alternative with either the highest or lowest contrast corresponding to the framing cue in each trial) with $77.3\pm0.01\%$ accuracy in all trials (chance level 33.3%; one-sided *t*-test against chance level: $t(19) = 33.22$, $p < 0.001$). Task framing did not influence the choice accuracy (two-sided *t*-test on the choice probability of the best alternative: $t(19) = 1.45$, $p = 0.16$, see Figure S2 in the Extended Data). However, participants responded faster in "Hig" framing trials (two-sided *t*-test on the *log*(RT): $t(19) = 2.44$, $p < 0.05$, see Figure S2 in the Extended Data).

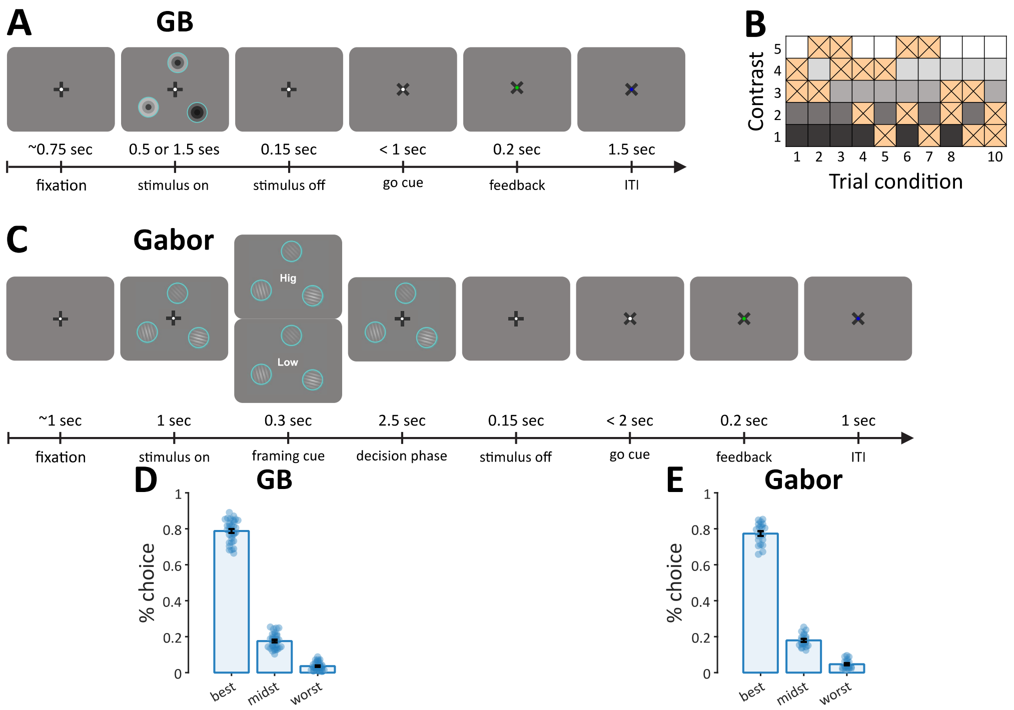

Figure 1. Task design and basic performance. (A) 3AFC perceptual task, GB*:* Each trial began with a fixation cue for a random delay. Following that, three alternatives were presented and stayed on the screen for either 0.5 or 1.5 seconds, in "short" or "long" trials respectively. Ceasing the stimuli presentation was followed by a short gap of 0.15 seconds, presenting the fixation cue. Immediately, a 45° rotation of the fixation cue signaled participants to report their choice by a button press within 1 second. The corresponding feedback promptly followed the reported choice, a change in the white spot on the fixation cue to green or red indicated a correct or wrong response. Then the trial closed with an inter-trial-interval (ITI) window lasting 1.5 seconds. **(B) Trial conditions:** Using the individualized just noticeable difference (JND), determined prior to the main task, we generated 5 contrast levels; 1 to 5 correspond to 0.5 + [-2JND, -JND, 0, JND, 2JND], respectively. We then created 10 distinct trial conditions by selecting permutations of 3 out these 5 levels. **(C) 3AFC perceptual task, Gabor:** Each trial began with a fixation cue presented for a random delay. Following this, three stimuli were displayed on the screen. After 1 second, a framing cue, labeled either "Low" or "Hig", replaced the fixation cue for 0.3 seconds to indicate the target contrast. Then, the fixation cue reappeared, marking the start of a 2.5-second decision phase. The stimulus presentation ended after the decision phase, and the fixation cue remained unchanged on the screen for 0.15 seconds. Immediately after, a 45° rotation of the fixation cue signaled participants to report their choice by pressing a button within 2 seconds. Following the participant's response, immediate feedback was provided. A change in the white spot on the fixation cue to green or red indicated a correct or incorrect response, respectively. Finally, the trial concluded with an inter-trial interval (ITI) window lasting 1 second. **(D-E)** Choice probability of each alternative, "best", "midst", and "worst" are defined relative to target contrast in any trial, the error bars indicate SEM across participants, and the dots are individual participants.

Lack of distractor effect on choice behavior

Having ensured that participants engaged well with both "GB" and "Gabor" tasks, we proceeded to investigate the influence of the distractor alternative on the relative choice probability of the other two high-value alternatives. Within a choice context including three alternatives, we designated the best, second-best, and distractor alternatives as “HV”, “LV”, and “DV”, respectively. Here we first analyzed the distractor effect in the “GB” and “Gabor” tasks separately. Next, to summarize the main effect and propose a computational mechanism, we pooled the data across these two experiments.

To examine the distractor effect, we included trials meeting specific criteria for the distractor effect analysis. Accordingly, we grouped the trials into two categories: 1) high-distractor and 2) low-distractor trials. In both of these two groups, the best and second-best alternatives have identical values, while only the distractor value varies. For example, in Figure 1B, we grouped trial conditions 4, 6, and 8 as “low-distractor” groups and 5, 7, and 9 as the corresponding “high-distractor” groups. We collapsed the data across the three trial conditions within each group since the different contrast levels of HV and LV did not yield any interactions on the main effect.

3AFC perceptual task, GB: Here we compared the relative choice share between two high-value alternatives (denoted as *P(HV over LV)*, see Equation 5) across the high-value and low-value distractor groups. To compute *P(HV over LV)*, we need to exclude the trials the distractor alternative was chosen (Figure 2A), resulting in almost $98.4 \pm 0.003\%$ and $95.9 \pm 0.005\%$ of trials in low-distractor and high-distractor groups to be considered for this analysis. However, the distractor alternative was not simply overlooked and the choice probability of a higher distractor is significantly higher than a lower distractor value (two-sided t-test: $t(31) = -9.42$, $p < 0.001$), the presence of a higher distractor value did not influence the choice behavior between two high-value alternatives, Figure 2B (two-sided t-test on distractor effect: $t(31) = 0.44$, $p = 0.66$), which is in contrast to the previous studies reporting either a negative or positive distractor effect on the choice share of two high-value alternatives (Chau et al., 2014, 2020; Itthipuripat et al., 2015; Louie et al., 2013). Our findings align with other studies reporting a null distractor effect on choice share between the two high-value alternatives (Gluth et al., 2020; Tohidi-Moghaddam & Tsetsos, 2025). Here we pooled data across all task factor manipulations, different stimulus durations, and eccentricity, given that there was no difference and interaction in the distractor effect between them (2-way ANOVA on the distractor effect: stimulus duration: $F(1,127) = 2.32$, $p = 0.13$, eccentricity: $F(1,127) = 0.05$, $p = 0.83$, interaction: $F(1,127) = 0.43$, $p = 0.51$, see Figure 2C).

3AFC perceptual task, Gabor: Here we also only included the trials in which either HV or LV were chosen, almost 97.3 $\pm$ 0.005% and 94.7 $\pm$ 0.006% of trials in low-distractor and high-distractor groups were considered for this analysis. Similar to the "GB" experiment, the higher distractor alternative was not simply ignored here (two-sided *t*-test: $t(19) = -7.21$, $p < 0.001$, Figure 2D) and the distractor effect on choice was also absent in the "Gabor" experiment, Figure 2E (two-sided *t*-test on distractor effect: $t(19) = 0.23$, $p = 0.82$). Given there was no difference in the distractor effect between task framings (two-sided *t*-test on distractor effect: $t(19) = 0.86$, $p = 0.4$, see Figure 2F), we also pooled data across the two framings.

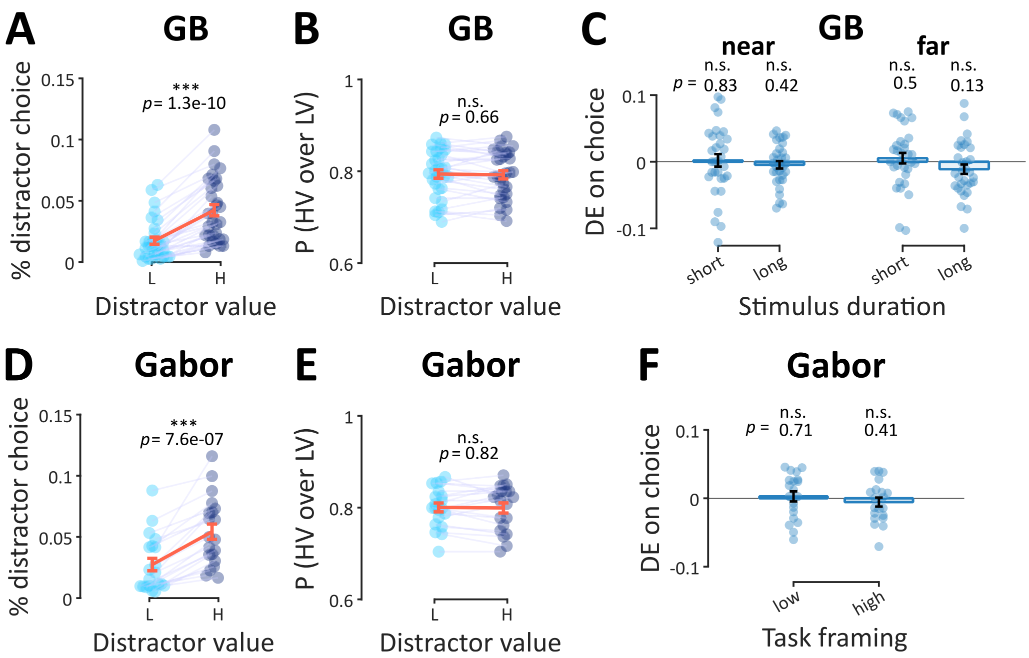

Figure 2. Distractor effect on choice. (A, D) Choice probability of distractor alternative. **(B, E)** Relative choice share or HV over LV in the "GB" and "Gabor" tasks as a function of distractor value. **(C, F)** The distractor effect demonstrated separately as a function of task factors within each experiment. Error bars in all panels indicate SEM across participants, and individual participants are represented by dots. Check Figure S4 in the Extended Data, for detailed analysis on the distractor effect on choice in any specific trial condition.

Prolonged decisions in the presence of a high-value distractor

3AFC perceptual task, GB: In contrast to the lack of distractor effect on choice behavior, we found that the reaction time (RT) of two high-value alternatives is significantly higher when the distractor value is high, we referred to it as the distractor effect on RT which is quantified as the difference between RT in high-distractor and low-distractor conditions (two-sided t-test on distractor effect on *log*(RT): $t(31) = -2.57$, $p < 0.05$). This finding is in agreement with the previous studies in the literature (Gluth et al., 2018, 2020). Here we also pooled data across all task factor manipulations, different stimulus durations, and eccentricity, given that there was no interaction and difference in the distractor effect on RT between them (2-way ANOVA on the distractor effect on *log*(RT): stimulus duration: $F(1,127) = 3.55$, $p = 0.06$, eccentricity: $F(1,127) = 3.9$, $p = 0.05$, interaction: $F(1,127) = 0.02$, $p = 0.88$, see Figure 3B).

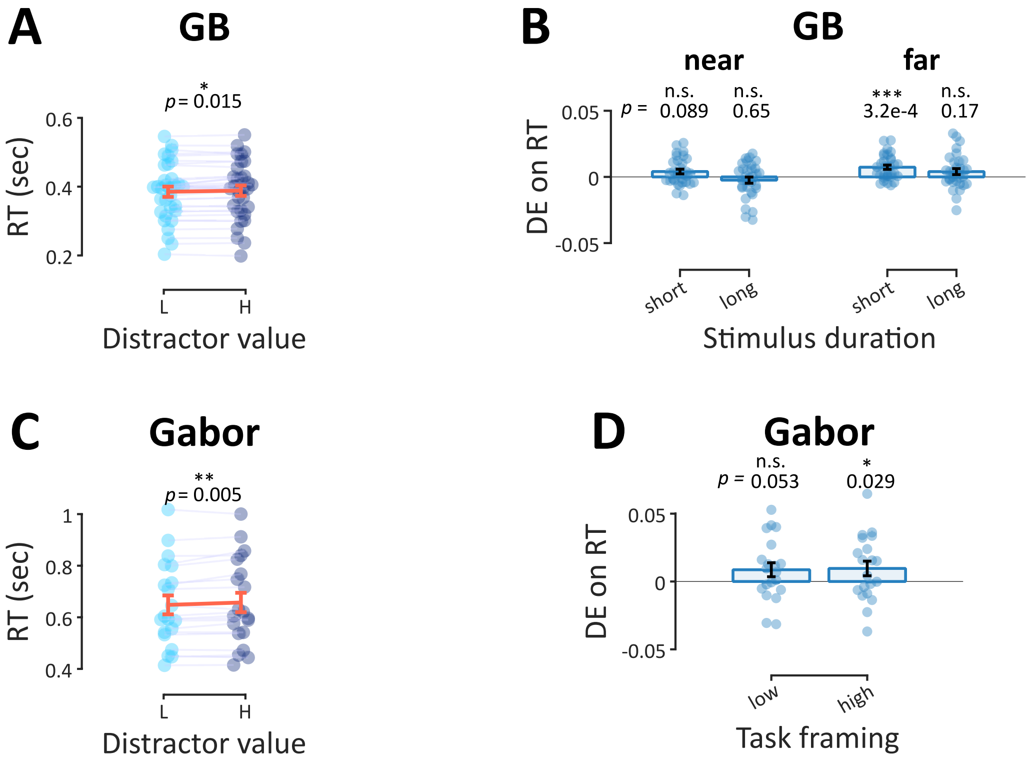

Figure 3. Distractor effect on RT. (A, C) Reaction time in the "GB" and "Gabor" tasks as a function of distractor value. **(B, D)** The distractor effect on RT, quantified as the RT in high-distractor trials minus low-distractor trials, demonstrated separately as a function of task factors within each experiment. Error bars in all panels are SEM across participants, and the dots indicate the individual participants. See Figure S4, for detailed analysis on the distractor effect on RT in any specific trial condition.

3AFC perceptual task, Gabor: Likewise, in Figure 3C we observed a negative distractor effect on the RT of two high-value alternatives in the "Gabor" experiments (two-sided t-test on distractor effect on *log*(RT): $t(19) = -3.17$, $p < 0.01$). The data was also pooled across task framings, given seeing no difference between two framings (two-sided *t*-test on distractor effect on *log*(RT) between framings: $t(19) = -0.31$, $p = 0.76$, see Figure 3D).

Computational modeling

Given the consistency between the "GB" and "Gabor" findings, here we first performed logistic regression analyses across two experiments for the distractor effect on choice and RT to summarize the main effects. Then we explored possible mechanisms underlying these behaviors. Finally, we proposed a computational model which could explain our results.

We first regressed the effect of each alternative on the relative choice share of two high-value alternatives. To do so, we performed a logistic regression analysis for each participant (Equation 9) and then we computed the statistical effect of each regressor on the dependent variable using a one-sample *t*-test on the estimated coefficients. In Figure 4A, we demonstrated that the higher difference between two high-value alternatives expectedly resulted in higher accuracy and there is no influence of the sum of two high-value alternatives on the accuracy (two-sided *t*-test on the beta coefficient of HV+LV: $t(51) = -1.09$, $p = 0.28$, on the beta coefficient of HV-LV: $t(51) = 24.57$, $p < 0.001$). This analysis further confirmed that the distractor alternative had a null effect on the choice share between two high-value alternatives (two-sided *t*-test on the beta coefficient of DV: $t(51) = -0.45$, $p = 0.65$).

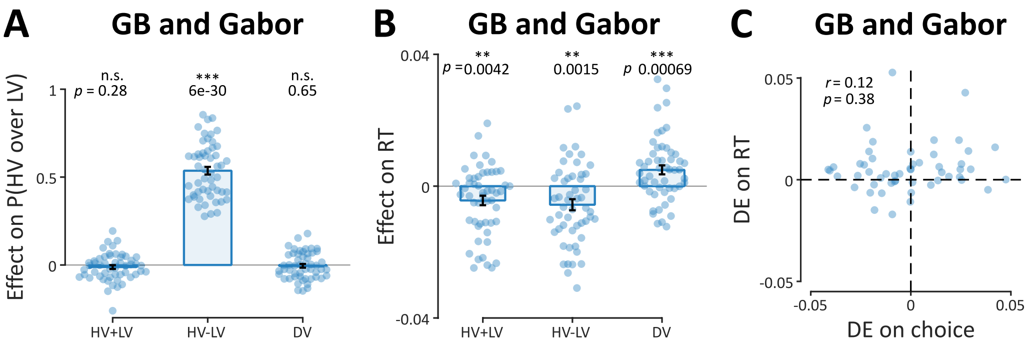

Figure 4. Distractor effect on choice and RT, using regression. (A, B) Beta coefficients of each regressor (in the x axis) indicating its effect on P (HV over LV) and RT in panel A and B respectively. **(C)** Correlation between the distractor effect on choice and RT. Error bars in both panels are SEM across participants, and the dots show the individual participants. See Figure S5 in the Extended Data, for the same result plotted separately for each experiment.

We next examined the distractor effect on RT using a regression analysis (Equation 9). In accordance with previous studies, expectedly, increasing the sum and difference of the two high-value alternatives accelerates the reaction time respectively (two-sided *t*-test on the beta coefficient of HV+LV: $t(51) = -2.99$, $p < 0.01$, on the beta coefficient of HV-LV: $t(51) = -3.35$, $p < 0.01$) (Teodorescu et al., 2016). Here we further affirmed that the presence of a higher distractor alternative slowed down the RT of the other two high-value alternatives (two-sided *t*-test on the beta coefficient of DV: $t(51) = 3.61$, $p < 0.001$). Figure 4C shows that the influence of the distractor on RT is independent of the direction of distractor effect (i.e., positive, null or negative) on the choice.

Seeing a null distractor effect on choice contradicts the divisive normalization theory, which is proposed as a canonical mechanism for context-dependent decision-making (Louie et al., 2011, 2013). However, this finding can be well explained by a baseline model, referred to here as the objective value (OV) model (see Figure S6, Equation 10). In the OV model, the context does not influence the value representation of the alternatives in the choice set; instead, subjective value is simply represented as the input value (i.e., objective value). Consequently, the context does not influence choice behavior (in Chapter 2, Figure 1, we explained how different models can lead to different subjective value representations and consequently result in various distractor effects (Tohidi-Moghaddam & Tsetsos, 2025)). Here, also in line with previous studies, if we assumed that the influence of the distractor on purely the choice behavior is the indicator of context-dependence in decision-making, we would conclude that the distractor effect has no effect on the decision-making process and a context-independent model could explain this choice behavior well (see the static model fits in Figure S6). However, given a significant distractor effect on RT, we cannot conclude that the distractor does not influence the decision-making process. Rather, dynamic models are needed to consider the influence of both choice and RT, which are 1- a null distractor effect on choice and 2- a negative distractor effect on RT in the presence of a higher distractor alternative. 3- The negative distractor effect on RT should be independent of the direction of the distractor effect on choice as we demonstrated in Figure 4C.

Drawing from the nature of the perceptual task and relevant literature, we propose that the underlying decision-making mechanism can be explained via a two-stage framework including (sensory) valuation and action. Our first framework suggests that the (sensory) valuation process involves a low-level normalization mechanism (Equation 11) in which all alternatives are normalized once immediately appear for the choice. These normalized values subsequently undergo a traditional drift-diffusion process, gradually accumulating evidence until meeting a decision threshold and prompting subsequent action (denoted as DN+ffi model, see Materials and Methods). The alternative framework posits a secondary valuation stage after normalization. Similar to our proposed framework in the previous chapter, this stage uses binary comparisons between pairs of alternatives in the choice set to identify the highest-value alternative and the final choice using a *softmax* function. Then, the value of the winning alternative undergoes a single race process, reaching the decision boundary for the corresponding final motor action and defining the RT. In this framework, the binary comparison stage can be modeled using either a rank-based (RB) (Equation 12) or a selective integration (SI) procedure (Equation 14) (denoted as DNRB+race and DNSI+race model, see Materials and Methods)

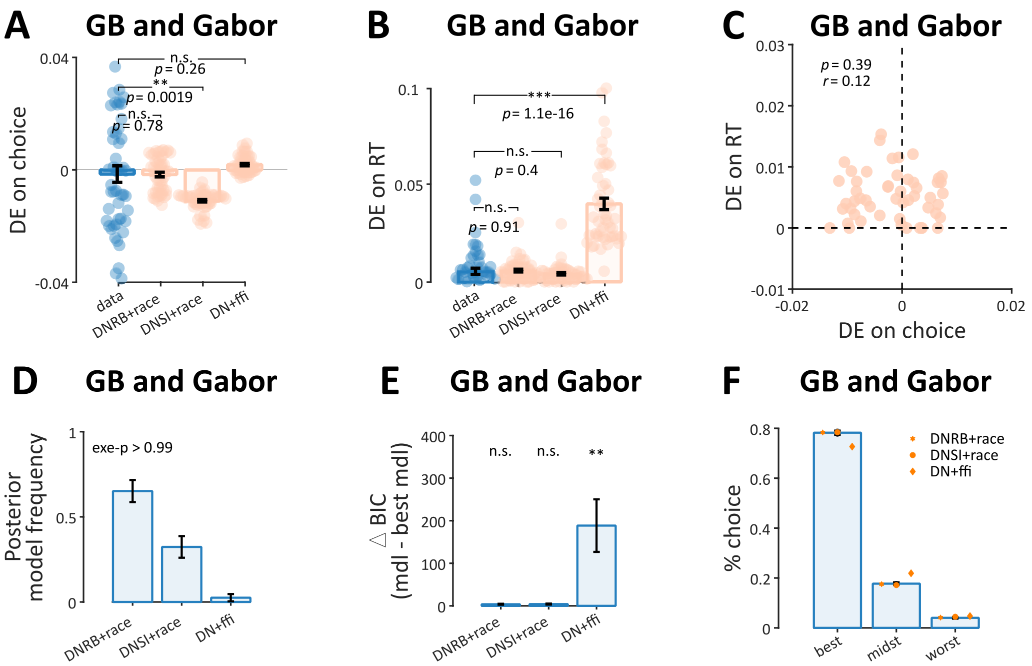

Figure 5. Model comparison. (A, B) Distractor effect on choice and RT, a comparison between the actual data and simulated data using the best-fitted parameters. **(C)** Correlation between the distractor effect on choice and RT, simulated by the best-fitted parameters of the DNRB+race model. **(D)** Random-effect Bayesian model comparison (Daunizeau et al., 2014; Rigoux et al., 2014). **(E)** Fixed-effect Bayesian model comparison, Black asterisks: significant ΔBIC against 10, one-sided one-sample *t*-tests (Kass & Raftery, 1995). **(F)** The simulated probability choice of each alternative superimposed on the actual data, simulated by the best-fitted parameters of each model. In all panels, the error bars are mean ± SEM across participants.

Figures 5A and 5B depict that the DNRB+race model provided a null distractor effect on choice and a significant negative distractor effect on RT respectively. Figure 5C shows that this model can predict the negative distractor effect independent of the distractor effect on choice. We show this by simulating choices using the best-fitted parameters of each model for each participant (see Table S1 in the Extended Data for the best-fitted parameters of each model). Here we also pooled the model predictions across both tasks given the consistent results (see Figure S7 in the Extended Data, a full comparison of all models). A further random-effects model comparison confirmed that the DNRB+race model accounted for the choice data (Figure 5D) better than the other alternative models (Daunizeau et al., 2014; Rigoux et al., 2014). A fixed-effects model comparison according to the BIC score (Kass & Raftery, 1995) shows that both DNRB+race and DNSI+race can equally explain the data in almost 48% of the participants and DN+ffi can only account for 4% of the participants.

The DNRB+race model effectively accounts for both negative and positive distractor effects on choice by integrating two functions: DN and RB. In both models, higher distractor values lead to more suppressed subjective values (see Figure 1 here: (Tohidi-Moghaddam & Tsetsos, 2025)). Finally, the model operates on the premise of a single "racer" for the final motor action, the winner (i.e., the alternative with the higher subjective value) in a high-distractor context takes longer to reach the decision threshold. Consequently, this delay in reaching the decision threshold results in a negative distractor effect on RT.

Pupil-linked arousal reflects the distractor effect on choice but not RT

It has been proposed that the global arousal state influences different brain areas involved in cognitive processes such as decision-making (Aston-Jones & Cohen, 2005; McGinley et al., 2015; Meyniel et al., 2015; Yu & Dayan, 2005). Thus, in the context of our task, the arousal system could influence the valuation and information sampling process in the presence of a distractor alternative, and consequently result in different distractor effects as a change in arousal. Therefore, here we tested whether the pupil response, as an indicator of the global arousal state of the brain, reflects any footprint of the distractor effect. To do this, we will look at the change in distractor effect on both choice and RT as a function of pupil response during the decision time (check Materials and Methods on how we defined the decision window for each study).

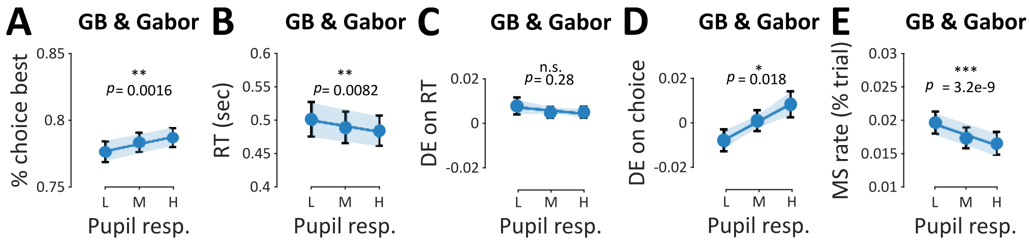

Figure 6. Pupil-linked arousal. (A, B) Choice probability of the best alternative and RT as the function of pupil response. **(C, D)** Distractor effect on RT and choice as the function of pupil response. **(E)** The relation between microsaccade rate and arousal. Error bars in all panels are SEM across participants, and the lines are the linear fits to data. See Figure S8-13 in Extended Data for any further analyses on the pupil response.

Previously, it has been suggested that the non-luminance fluctuations in pupil diameter at constant luminance are related to the central arousal state (de Gee et al., 2014; De Gee et al., 2020; Reimer et al., 2014; Urai et al., 2017; Vinck et al., 2015). Here, we used the average pupil diameter during decision time (see Figure S8 in the Extended Data for the pupil dilation across trials), referred to as the pupil response (see Materials and Methods). In Figures 6A and 6B, we first showed that participants performed more accurately and faster as arousal increased (one-sample one sided t-test on the beta coefficient of pb in Equation 9 for the probability of choice in Figure 6A: $t(51) = 3.09$, $p < 0.01$ and RT in Figure 6B: $t(51) = -2.48$, $p < 0.01$). Again, the data were pooled across two experiments due to the consistent pattern of distractor effect on choice and RT (see Figure S9 in the Extended Data for each experiment). In Figures 6C and 6D, we have illustrated that the pupil response does not reflect a change in the distractor effect on RT, but interestingly, the pupil response linearly tracks a shift from a negative distractor effect to a positive distractor effect on choice (one-sample one sided t-test on the beta coefficient of pb in Equation 9 for the distractor effect on RT in Figure 6C: $t(51) = -0.58$, $p = 0.28$ and choice in Figure 6D: $t(51) = 2.14$, $p < 0.05$). This finding suggests that the decision process and evaluation in a multi-alternative task may also be modulated by arousal state.

The model we proposed also operates between two modes: a negative (via low-level divisive normalization) and a positive distractor effect (via high-level binary comparisons) on choice. Thus, this result can indicate that, under lower arousal, normalization has a greater impact on value representation, resulting in a negative distractor effect on choice. On the other hand, higher arousal indicates a greater cognitive process based on memory binary comparisons for the valuation stage, yielding an overall positive distractor effect on choice. In Figure 6E, we also showed that the microsaccade rate decreased as a function of arousal (i.e., pupil response) (one-sample one-sided t-test on the beta coefficient of *pb* in Equation 9 for the microsaccade rate in Figure 6E: $t(51) = -6.95$, $p < 0.001$). This could be further evidence supporting higher cognitive processes as a function of higher arousal since it has been proposed that the microsaccade rate decreases with higher cognitive effort (Krejtz et al., 2018, 2020; Siegenthaler et al., 2014). However, detecting microsaccades under higher arousal introduces confounding factors due to the larger pupil diameter.

Discussion

In the realm of complex multi-alternative decisions, individuals frequently deviate from the Independence of Irrelevant Alternatives (IIA), a cornerstone axiom of rational choice theory (Luce, 1959, 1977). This violation sparks an ongoing debate regarding the influence of distractor alternatives on the decision-making process. Recent studies using value-based decision tasks have presented conflicting evidence, with some suggesting that distractors can enhance choice accuracy (Chau et al., 2020), while others propose that they may impede it (Itthipuripat et al., 2015; Louie et al., 2013). Interestingly, a few studies support IIA, but decisions tend to slow down when more distractors are present. Here we delved into the formation of the distractor effect empirically and theoretically using two simple perceptual tasks (Gluth et al., 2018, 2020). We initiated our investigation by employing a novel perceptual task to first assess the generalizability of the distractor effect and then reconsider the normalization theory as a predominant mechanism driving the distractor effect. This task also allowed us to explore how the immediate context affects choice behavior, which has been a topic of debate in the literature (Louie & De Martino, 2014; Madan et al., 2021). Furthermore, conducting simpler tasks enabled us to control the complexity of the decision-making process effectively and facilitated the formulation of a computational framework.

We collected data from two different perceptual tasks. In both datasets, we demonstrated the consistent patterns of the absence of a distractor effect on choice and prolonged decisions in the presence of a higher distractor, called the negative distractor effect on response time. Due to the observed impact on response time (RT) rather than the choice itself, we have ruled out the feasibility of purely static models in explaining distractor effects on decision-making. Instead, we proposed that adopting traditional dynamic models, which not only encompass the general decision-making processes (Bogacz et al., 2006; Usher & McClelland, 2001), but also can handle the nuances of these complex multi-alternative tasks can better capture both the choice and RT effects. We introduced an expanded race model comprising valuation and action stages, which offer ways to account for the effects we observed. The valuation stage incorporates the value representation of each alternative. Immediately it follows the action stage to finalize the decision-making process for the preferred alternative, implemented via a single racer to meet the decision bound and conclude the motor action.

One novel finding in our study was that the phasic arousal during decision-making modulated the distractor effect on choice. Testing the influence of arousal on choice biases has been a recent line of research in decision-making neuroscience (de Gee et al., 2014; De Gee et al., 2020; Hebisch et al., 2024; Nuiten et al., 2025; Urai et al., 2017, 2019). Higher arousal states have been shown to linearly influence choice biases in sensory detection tasks (De Gee et al., 2020; Nuiten et al., 2025; Urai et al., 2017). Assuming that the distractor effect is a bias that violates rational choice theories, we also examined the impact of arousal on distractor effect. Interestingly, we showed that the direction of the distractor effect shifted from negative to positive as arousal increased. We interpreted that at lower arousal, the evaluation stage may be modulated mainly by low-level normalization encoding, resulting in a negative distractor effect. In contrast, higher arousal might represent higher-level cognitive processes such as memory-based binary computations, resulting in a positive distractor effect. This can be explained by the properties of our proposed model, which allows for the interplay between divisive normalization and memory-based binary comparisons, resulting in negative and positive distractor effects, respectively. These observations are also consistent with the behavioral findings of Chau et al. (Chau et al., 2020) who reported a negative distractor effect on easy trials but a positive distractor effect on difficult trials. This shift can be interpreted as reflecting the differential recruitment of cognitive resources. Easy trials may be resolved through automatic, low-level mechanisms (e.g., perceptual heuristics or normalization), whereas harder trials require more effortful, high-level processing that possibly invokes attention, and working memory. Our findings extend this idea by suggesting that arousal itself modulates cognitive processes such as decision-making. Therefore, the role of arousal should be considered in future computational modeling.

We concluded that the distractor alternative exerts context-dependent effects on the decision-making process. This influence may manifest as either an explicit impact on the ultimate choice or as an implicit impact on the response time via distinct value representations in different contexts. The neural findings align with the latter notions, although we do not reject the former proposition, as the final choice is influenced by the initial value representation. Indeed, we propose that tracking the entire information sampling process, rather than solely focusing on the final action taken, would offer valuable insights into understanding the decision-making process and the formation of distractor effects.

Materials and Methods

Task and Datasets

We analyzed two distinct datasets, each comprising a three-alternative forced-choice (3AFC) perceptual task. In one task, the perceptual stimuli were Gaussian blobs, while in the other task, Gabor patches were used as stimuli. For clarity throughout here and the main text, we refer to them as the “3AFC perceptual task: GB” or only “GB” and the “3AFC perceptual task: Gabor” or “Gabor”, respectively. In both tasks, participants were presented with three perceptual alternatives simultaneously on the screen for a fixed duration. Participants were instructed to report their decision following a go cue and before the response window deadline. The correct decision in the “GB” task was always defined as the alternative with the highest contrast. In contrast, in the “Gabor” task, the correct decision was determined by the framing cue presented in the middle of the trial, which could indicate either the highest or lowest contrast. The "GB" dataset was collected in a behavioral laboratory while pupillometry was only measured. The "Gabor" dataset was collected in a different laboratory where pupillometry and magnetoencephalography (MEG) signals were recorded simultaneously. Since this chapter focuses on analyzing behavioral and pupillometry data from these two datasets, the following describes how the behavioral task and pupillometry were conducted.

3AFC perceptual task: GB

Participants and Procedure

We recruited thirty-two participants (23 female and 9 male, age range: 21-35) from the internal participant pool in the Institute of Neurophysiology and Pathophysiology of the University Medical Center Hamburg-Eppendorf. Before starting the experiment, all participants gave written informed consent. The study was approved by the local ethics committee of the Hamburg Medical Association. All participants had normal or corrected-to-normal vision and were right-handed, except two left-handed participants. The experimental session lasted between 2.5 and 3 hrs and was broken down into 16 blocks, with each block lasting ~9 minutes. Participants had the opportunity to take short breaks (< 1 minute) between blocks and one or two longer breaks (5-10 minutes) upon request. Participants received 25-30 EUR for their participation (hourly net rate = 10 EUR). In addition, we included a 10 EUR completion bonus.

Main task

The task was implemented using Psychophysics-3 Toolbox in Matlab (MathWorks, 2019) on a 21” monitor with a screen resolution of 1920 x 1080 pixels and a refresh rate of 120 Hz. Stimuli were presented on a grey background [127.5 127.5 127.5] in a dimly lit room, with participants seated 60 cm away from the monitor. Participants completed a three-alternative perceptual decision-making task consisting of 16 blocks of 120 trials. They were instructed to choose the stimulus with the highest contrast in each trial. Each trial started with the presentation of a fixation cue for a random short delay (randomly drawn from a truncated exponential distribution: [0.5 1] and mean = 0.75 seconds). The three stimuli then appeared on the screen, positioned equidistantly, at the top, left, and right, from the fixation cue (To mitigate bias toward the top stimulus, we tilted the entire array of stimuli either 6 degrees clockwise or counterclockwise). This tilt was randomized and counterbalanced between participants. In “Far” blocks, the eccentricity was set to 2.2 visual degrees, while in “Near” blocks, it was adjusted to 1.25 visual degrees. We presented 8 “Far” and 8 “Near” blocks alternatively interleaved. The type of starting block for each experiment session was randomly assigned and counterbalanced between participants. The stimuli presentation ended either after 0.5 seconds (in “short” trials) or 1.5 seconds (in “long” trials), randomly determined and counterbalanced within each block. Then, the stimulus presentation stopped, followed by a short gap in which the fixation cue remained on the screen for 0.15 seconds. Immediately after, the response window began, cued by a 45° rotation of the central fixation, prompting participants to report their choice with a button press. The participants used their index, middle, and ring fingers of the right hand to press the left, up, and right arrow keys, respectively, indicating a left, top, and right choice response. The reported choice was promptly followed by corresponding feedback lasting 0.2 seconds. A change in the white spot on the fixation cue to green and red signaled the correct and wrong decisions, respectively. The response window had a maximum duration of 1 second. Failure to respond within this timeframe triggered a “Missed response” message on the screen during the feedback window. The trial ended with a 1.5-second inter-trial interval (ITI), following the feedback window.

Stimuli

The Stimuli were 2-dimensional (2D) Gaussian blob patches (diameter = 1.6 visual degrees). The colors of the stimuli were either black or white, they were randomized and counterbalanced across participants. We generated each patch using the following 2D Gaussian function:

$$G_\sigma(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}}, \tag{1}$$

where σ was equal to 0.4 visual degrees. Then to produce the white and black patches with different contrasts we applied the following function denoted in equation 2:

$$GB\ patch = 0.5 * (1 + G_\sigma(x, y) * BW * c), \tag{2}$$

Where *BW* is a parameter controlling the color of the patch (0 for black and 1 for white) and *c* is the patch contrast, from this range: [0 1]. The contrast of three stimuli in each trial was drawn without replacement from a set of five contrast levels, resulting in 10 possible permutations or trial types. We linearly spaced the five contrast levels, starting from 0.5, using an individualized just noticeable difference (JND). Prior to the main task, participants completed one or a maximum of two blocks (120 trials) of a binary detection task following a staircase procedure. There, we adjusted the individualized JND at a 75% accuracy detection threshold.

3AFC perceptual task: Gabor

Participants and Procedure

Twenty participants (9 female and 11 male, aged between 21 and 35) were recruited from the internal participant pool at the Institute of Neurophysiology and Pathophysiology of the University Medical Center Hamburg-Eppendorf. The study protocol received approval from the local ethics committee of the Hamburg Medical Prior to the experiment, all participants provided written informed consent; they were healthy human beings and had normal or corrected-to-normal vision. During the experiment, participants completed 18 blocks, with each block lasting approximately 12 minutes. We allowed short breaks, less than a minute long, between blocks. Additionally, participants could request longer breaks, lasting between 5 to 10 minutes, as needed. To appreciate their time and effort, participants received compensation. This compensation included an hourly net rate of 10 EUR, along with a completion task bonus.

Main task

The task was conducted using the Psychophysics-3 Toolbox in Matlab (The MathWorks Inc., 2022). Stimuli were displayed on a grey background [127.5 127.5 127.5] in a dimly lit room, with participants seated 56 cm away from the monitor. Participants engaged in a three-alternative perceptual decision-making task, including 18 blocks of 120 trials. In this task, participants were instructed to select the target stimulus (i.e., alternative) based on a framing cue indicating either the highest or lowest contrast in each trial. Each trial began with the presentation of a fixation cue, preceded by a random short delay drawn from a normal distribution ([0.75 1.25] seconds, mean = 1 second). Three stimuli then appeared on the screen, equidistantly positioned (2.2 visual degrees) at the top, left, and right of the fixation cue. To mitigate bias toward the top stimulus, the entire array of stimuli was tilted either 6 degrees clockwise or counterclockwise. This tilt was randomized and counterbalanced between participants. After one second of stimulus presentation, the fixation cue was replaced by a framing cue indicating the target contrast (either "Hig" for highest or "Low" for lowest) for 0.3 seconds. The framing cue was randomized across trials. Following the framing cue, the fixation cue reappeared, marking the start of a 2.5-second decision phase. Throughout this 3.8-second interval (stimulus onset to end of decision phase), all three stimuli remained on the screen. After the stimulus presentation ended, there was a short gap during which the fixation cue remained on the screen for 0.15 seconds. Subsequently, the response window was initiated, signaled by a 45° rotation of the central fixation point. Participants were instructed to report their choice using button presses (left thumb, right thumb, or foot button press for left, right, or top option, respectively) within the response window, a maximum of 3 seconds. The foot assigned to the top alternative was randomized across participants. Feedback was promptly provided after each response, indicated by a change in the color of the fixation cue (white to green for correct and white to red for incorrect decisions). Failure to respond within the 3-second window triggered a "Missed response" message during the feedback window. Finally, a 1-second inter-trial interval followed the feedback window, concluding each trial.

Stimuli

The stimuli used in the experiment were 2-dimensional (2D) Gabor patches with a diameter of 1.6 visual degrees. These patches were presented in either black or white colors, with their assignments randomized and counterbalanced across participants. To generate the Gabor patches, we first created a Gaussian patch using Equation 1. Each Gabor patch was then produced using the following equation:

$$Gabor = \sin(2\pi f) * G_{\sigma}(x, y) \tag{3}$$

The spatial frequency of the Gabor patch, denoted as f, was set to 4 cycles per visual degree. To generate Gabor patches with varying contrasts in both white and black colors, we applied the following function, as denoted in Equation 4:

$$Gabor\,patch = 0.5 * (1 + Gabor * BW * c), \tag{4}$$

here BW controlled the color of the patch (0 for black, 1 for white), and c represented the patch's contrast, ranging from 0 to 1. For each trial, the contrasts of the three stimuli were randomly selected without replacement from a set of five contrast levels. This procedure resulted in 10 possible trial conditions. The five contrast levels were linearly spaced, beginning from 0.5, and were determined based on an individualized just noticeable difference (JND). Before starting the main task, participants underwent one or a maximum of two blocks (120 trials) of a binary detection task. This task utilized a staircase procedure (Cornsweet, 1962; Levitt, 1971) to adjust the individualized JND to achieve a 75% accuracy detection threshold. The stimuli were oriented Gabor patches and we used this orientation set: [15°, 45°, 75°] to assign an orientation to them. Two trial types were defined based on orientation: "homogeneous" and "heterogeneous". In "homogeneous" trials, all three stimuli shared the same orientation, while in "heterogeneous" trials, each stimulus had a distinct orientation.

Behavioral Analyses

Relative choice: To quantify the distractor effect we compared the relative choice between the two groups of trials with the high-value and low-value distractors. The relative choice quantifies the choice share of the two high-value alternatives (best as "HV" and second-best as "LV") relative to each other:

$$p(HV\ over\ LV) = \frac{p(HV)}{p(HV) + p(LV)}, \tag{5}$$

where *p(HV)* and *p(LV)* indicate the choice probability of the best and second-best alternatives.

The distractor effect on choice is quantified as:

$$DE\_choice = p(HV\ over\ LV|high\_D) - p(HV\ over\ LV|low\_D) \quad (6)$$

Similarly, we computed the distractor effect on RT as:

$$DE\_rt = rt(either\ HV\ or\ LV|\ high\_D) - rt(either\ HV\ or\ LV|low\_D) \quad (7)$$

Thus, *DE > 0*, *DE < 0*, and, *DE = 0*, indicate a negative, a positive, and a null distractor effect respectively. Note that the sign of *DE_rt* here is not consistent with the terms we used, because when the difference is positive, it means that RT is hindered more in the presence of a higher distractor alternative.

We further employed a logistic regression analysis to parametrically examine the distractor effect on choice and RT as:

$$y \sim \beta_0 + \beta_1(HV + LV) + \beta_2(HV - LV) + \beta_3 DV, \quad (8)$$

where, *HV*, *LV* and *DV* are the contrast level of each alternative in the choice set and we estimated the beta coefficients for each participant using the *glmfit* function in MATLAB.

We only analyzed trials in which participants responded within the deadline of the response window. In the results section, we reported the mean with standard errors-of-mean (SEM) across participants. Depending on the appropriate test for each analysis, the statistical effects were examined using one-sample *t*-tests, *F*-test using ANOVA, and Pearson correlation. All analyses were done using MATLAB (The MathWorks Inc., 2022).

Pupillometry

Pre-processing: We tracked pupil dilation, horizontal and vertical gaze positions at a sampling rate of 1000 Hz using an EyeLink 1000 (SR Research Ltd.) in both behavioral and MEG laboratories. The eye-tracker was calibrated at the beginning of each block. For preprocessing the pupil time series within each block, we employed FieldTrip (Oostenveld et al., 2011) and custom-made Matlab scripts (Urai et al., 2017). Missing data points resulting from blinks and saccades, as detected by the EyeLink software, were interpolated from -150 ms to 150 ms around the missing data. Subsequently, the effect of blinks and saccades on the pupil response was estimated through deconvolution and removed from the data using linear regression (Knapen et al., 2016). The residual pupil time series were then band-pass filtered using a third-order Butterworth filter with cut-off frequencies of 0.01 to 6 Hz, z-scored per block of trials, and down-sampled to 50 Hz. To capture changes in pupil diameter, we computed the first temporal derivative of pupil diameter by subtracting adjacent frames and applied a low-pass filter with a cut-off frequency of 2 Hz (De Gee et al., 2020).

We included all trials from all participants in the analyses reported in this chapter. The only exception was seven blocks from one participant in the behavioral laboratory, which were excluded due to issues with the eye tracker during data collection.

Pupil response: To analyze the pupil response in each trial, the trials were epoched and baseline correction was performed by subtracting the mean pupil diameter from 500 milliseconds before stimulus onset. The average pupil diameter during the decision-making window was calculated and referred to as the pupil response for arousal analysis. For the "GB" dataset in both “short” and “long” trials, we considered the entire stimulus window to be the decision-making window. Due to the long stimulus presentation in the "Gabor" task and the high phasic response after framing onset (see Figure S8 in the Extended Data for pupil dilation over the entire trial), we defined the decision-making window as 1-second after framing onset. We also analyzed the data considering the entire stimulus presentation, and the results are shown in Figure S10 in the Extended Data.

Arousal analysis: To investigate the influence of arousal on behavior, we looked the the corresponding behavior metric as the function pupil response. To achieve so, we first binned the average pupil response into three bins, then we used the following linear regression approach to quantify the influence of pupil response on the corresponding behavior metric:

$$y \sim \beta_0 + \beta_1 pb, \tag{9}$$

where *pb* is the bin number, we estimated the beta coefficients for each participant using the *polyfit* function in MATLAB.

According to the definitions of phasic and tonic arousal (Nuiten et al., 2025), the focus of this chapter was on the influence of phasic arousal on the distractor effect during the decision-making process. However, we further examined the impact of tonic arousal, which is defined as the mean pupil response 500 milliseconds before stimulus onset. Figure S11 in the Extended Data shows that tonic arousal does not modulate the distractor effect.

Microsaccade analysis: Microsaccades are defined as events with high gaze velocity. We quantified gaze velocity as the absolute value of the temporal derivative over the x-y coordinates, which was then smoothed using a 0.02-second Gaussian kernel. We recorded a microsaccade when the velocity exceeded three times the trial-based median. To avoid counting the same event multiple times, we imposed a minimum delay of 40 milliseconds between gaze shifts. We calculated the microsaccade rate as the saccade probability over trials at each sample (B. Liu et al., 2024).

Computational Models

We assumed that the decision-making process comprises two main stages: valuation and decision. To elucidate the computational mechanism underlying the evaluation of the value for each alternative, resulting in a subjective value (*SV*) for each, we employed a range of context-dependent and baseline models. These *SV*s are passed as inputs to the decision model, enabling us to explain choice and reaction time (RT) behaviors. We used both static and dynamic decision models, while a static decision model allowed us to exclusively explain choice behavior, employing a dynamic decision model enabled us to model choice and RT behavior simultaneously.

Value evaluation models

We used the following computational models with each describing an alternative mechanism mapping objective value into their subjective (transformed) counterparts.

Objective value model (OV): This model assumes that the subjective values should be unaffected by the choice-set context. Thus, there is no transformation in this model and the subjective values (*SV*) are encoded as equal to the objective values (*OV*).

$$SV_i = OV_i \qquad (10)$$

Divisive normalization model (DN): The subjective value of each alternative is normalized by the sum of all alternatives.

$$SV_i = \frac{OV_i}{1 + w * \sum_{n=1}^{3} OV_n}, \qquad (11)$$

where *w* is the weight term and was constrained to this range, [0.1 1] while fitting the model to the actual human data.

Rank-based model (RB): This model implements relative value coding using a series of memory-based binary comparisons across all possible pairs of alternatives in the context. The subjective value of each alternative is the total number of times that this alternative was the winner across all memory-based binary comparisons.

$$SV_i = nc * \sum_{j \neq i}^{n-1} p_{(i>j)}, \qquad (12)$$

where *nc* represents the total number of binary comparisons, constrained in the [1 200] range. $P_{(i>j)}$ is the probability that alternative *i* is deemed as better than alternative *j* in a given binary comparison. We derived this probability using a softmax function:

$$p_{(i>j)} = \frac{\exp(\beta * OV_i)}{\exp(\beta * OV_i) + \exp(\beta * OV_j)}, \qquad (13)$$

where β is the inverse temperature parameter, which was constrained in the [1e-4 100] range when fitting the model.

Selective integration model (SI): This model assumes that each objective value is weighted based on its relative difference with the other alternatives in the choice set as below:

$$SV_i = OV_i * \frac{\sum_{j \neq i}^{n-1} w_{ij}}{n-1} \qquad (14)$$

where w_{ij} is a gaiting variable and calculated through a logistic function:

$$w_{ij} = \frac{1}{1 + \exp\left(-\beta * (OV_i - OV_j)\right)}, \tag{15}$$

β is the variable controlling the degree to which the difference between the two input values reduces the influence of those input values. This was constrained in the [1e-4 100] range when fitting the model.

According to the nature of our tasks, we further hypothesized that there may be a first sensory stage prior to the valuation stage. The sensory stage can be a low-level divisive normalization mechanism that passes the normalized objective values to the next valuation stage for further computation. Here, the next valuation stage can be an RB or SI model, denoted as DNRB and DNSI models, respectively. To model these two extensions, we first computed the normalized objective values using Equation 11 and passed them to the RB (Equation 12) and SI (Equation 14) models as inputs to compute the subjective values.

Static decision model

To model the choice behavior solely we used a softmax function. This function takes the subjective values (*SV*), derived from the value evaluation models, as inputs and calculates the choice probability for each alternative. For each alternative *i* the choice probability *p(i)* was calculated as:

$$p(ch = i) = \frac{\exp\left(\beta * SV_i\right)}{\sum_{j=1}^{n} \exp\left(\beta * OV_j\right)}, \tag{16}$$

where β is the inverse temperature parameter constrained in the [1e-4 20] range when fitting the model.

Dynamic decision-action model

We adopted two dynamic choice models to explain the choice behavior simultaneously with the RT for multi-alternative tasks. We first used a feedforward inhibition (FFI) framework, in which there are as many accumulators as the number of alternatives in the choice set. Each accumulator is excited by evidence supporting one alternative while being inhibited by evidence favoring the other alternatives. Thus, this framework controls the full interaction between alternatives, while it has the property of combining features of both the drift-diffusion and the race model (including 3 racers). We then assumed that in these fixed-duration tasks, the choice could be concluded during the stimulus presentation. Subsequently, only one racer is needed to receive the *SV* of the chosen alternative and complete the motor action only. We extended the analytical solution of FFI to implement this one-racer idea.

Feedforward inhibition model (FFI): In this model, each accumulator is an ideal integrator without any leak over time, receiving the excitation input from the corresponding alternative and inhibition input from the other alternatives. Each integrator (x_i) activates as below:

$$dx_i = (k * I_i + I_0) * dt, \qquad (17)$$

where k is the drift rate parameter (i.e., sensitivity) and I_0 is a baseline input. I_i, the evidence accumulated for each alternative, is calculated as below:

$$I_i = SV_i - c * (\frac{\sum_{i \neq j} SV_j}{n-1}) \qquad (18)$$

where SV_i represents the subjective value obtained from the valuation stage for the i^{th} alternative. C serves as the FFI strength parameter, regulating the interpolation between a race and drift-diffusion model. To fit the model, we allowed this parameter to vary within the range [0 1]. Fixing c to 0 yields a classic race model, while a value of 1 makes it behave like a drift-diffusion model. Thus, the drift of FFI can be computed as:

$$\mu_i = k * \left(SV_i - c * (\frac{\sum_{i \neq j} SV_j}{n-1}) \right) + I_0 \qquad (19)$$

To fit the model we used the established analytical solution for the FFI dynamic function (Usher et al., 2002) and extended the scripts used in this paper (Cao & Tsetsos, 2022b). This analytical solution suggests that the distribution of arrival times can be explained using a Wald distribution:

$$g(\theta, t) = \frac{\theta}{\sqrt{2\pi\sigma^2 t^3}} \exp\left(-\frac{(\theta - \mu t)^2}{2\sigma^2 t}\right), \tag{20}$$

where θ is the threshold (i.e., decision boundary) and σ^2 is the variance of the diffusion process, fixed to 1 while fitting the models. Accordingly, for a given trial the probability of seeing an $RT = T_d + T_{nd}$ is:

$$p(t = RT) = \frac{\theta}{\sqrt{2\pi\sigma^2 T_d^3}} \exp\left(-\frac{(\theta - \mu T_d)^2}{2\sigma^2 T_d}\right), \tag{21}$$

Then the probability of observing a response *i* (i.e., choice) but not the others ($j \neq i$) at a given *RT* is defined as only i^{th} accumulator reaches the threshold at $t = RT$ and none of the other accumulators has reached the decision threshold yet. It can be formulated as below:

$$p(t = RT, ch = i) = p(t_i = RT). \prod_{j \neq i}^{n-1} p(t_j > RT) \tag{22}$$

Oner-racer model (race): In this model, we assumed that after the value stage, the maximum subjective value is chosen as the final choice, and then it passed to a single diffusion process to reach the decision boundary at a certain time for the appropriate action selection. To implement this model, we first calculated the choice probability for each alternative as denoted in Equation 12 and the distribution of arrival time can be explained by a Wald distribution denoted in Equation 17. So, we proposed that the likelihood of observing a given *RT* for a response *i* is:

$$L(t = RT, ch = i) = p(t_i = RT). p(ch = i) \tag{23}$$

Model fitting procedure: We fitted the models by minimizing the negative log-likelihood (*NLL*) summed over all choice trials (including all ternary and binary trials) (Wilson & Collins, 2019). For each participant, we fitted each model once on the entire set of trials (~1920 trials in GB ~2160 trials in Gabor). We optimized the parameters using Matlab's *fmincon.m* function (MaxFunEvals = 5000; MaxIter = 5000; TolFun = 1e-10; TolX = 1e-10). To avoid local optima, we refitted each model for each participant 10 times using a grid of randomly generated starting values for the free parameters.

Model selection: We used a fixed-effects and a random-effects model comparison. We used the Bayesian information criterion (*BIC*) to compare different models. The *BIC* is quantified as below:

$$BIC = k * \ln(n) - 2 * \ln(L) \tag{24}$$

where *L* is the likelihood value obtained from the model fit to all choice data, *k* is the number of free parameters in each model and *n* is the number of trials we used to fit the model (Schwarz, 1978). We computed the *BIC* score for each participant and each model. Then for each participant, the model with the lowest *BIC* was marked as the best-individualized model. Finally, we reported the *ΔBIC* of each model relative to the best-individualized model.

We also fitted the models using a 5-fold cross-validation procedure. To do so, for each participant, we split the trials into 5 parts (i.e., folds) and then fitted each model to a "training" set (comprising five random folds). We used the best-fitted parameters of the "training" set to calculate the *LL* summed across trials in the left-out "test" fold. We repeated this process over test folds (5 times) and the final cross-validated *LL* was computed as the mean *LL* across cross-validated folds. We then used this mean *LL* to calculate each model's posterior frequency and protected exceedance probability (i.e., the probability corrected for the chance level that a model is more likely than any others) using the variational Bayesian analysis (VBA) toolbox (Daunizeau et al., 2014; Rigoux et al., 2014).

Acknowledgments

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Extended Data

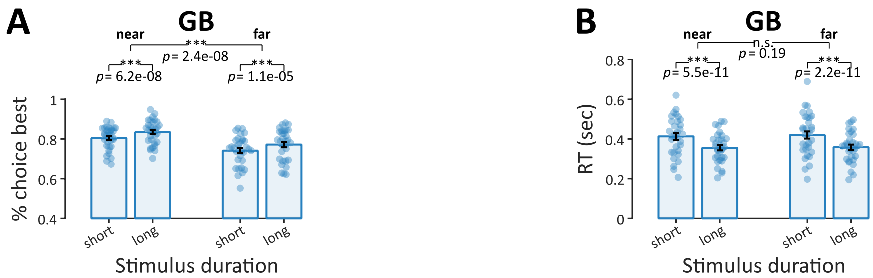

Figure S1. Basic task performance in the 3AFC perceptual task, GB. (A) Choice accuracy was significantly lower in "short" trials (two-sided *t*-test on the choice probability of the best alternative "short" vs. "long" trials: $t(31) = -7.67$, $p < 0.001$) and it was higher in "near" trials (two-sided *t*-test on "near" vs. "far" trials: $t(31) = 7.40$, $p < 0.001$). **(B)** Participants responded faster in the "long" trials (two-sided *t*-test on the *log*(RT) "short" vs. "long" trials: $t(31) = 10.16$, $p < 0.001$) and there was no difference between "near" and "far" trials (two-sided *t*-test on the *log*(RT) "near" vs. "far" trials: $t(31) = -1.33$, $p = 0.19$). The error bars indicate SEM across participants, and the dots are individual participants.

Figure S2. Basic task performance in the 3AFC perceptual task, Gabor. (A) Choice accuracy did not change as the function of task framing (two-sided *t*-test on the choice probability of the best alternative "low" vs. "high" framing trials: $t(19) = 1.45$, $p = 0.16$). **(B)** Participants responded faster in the "high" framing trials (two-sided *t*-test on the *log*(RT) "low" vs. "high" framing trials: $t(19) = 2.44$, $p < 0.05$). The error bars indicate SEM across participants, and the dots are individual participants.

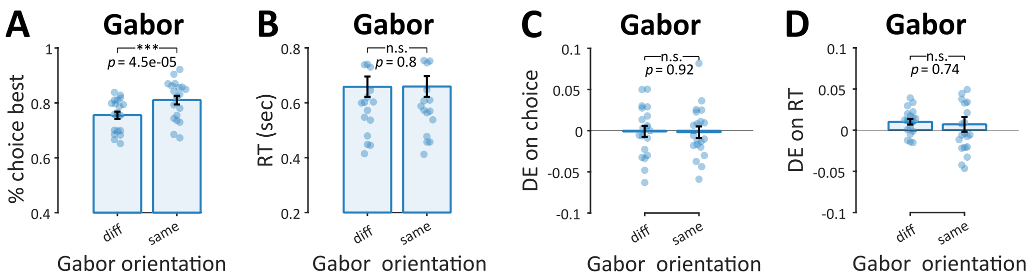

Figure S3. Behavioral analyses as the function of the Gabor orientations. (A) Choice accuracy was higher in "same" trials (two-sided *t*-test on the choice probability of the best alternative "diff" vs. "same" trials: $t(19) = -5.26$, $p < 0.001$). **(B)** Reaction time did not change between two groups of trials (two-sided *t*-test on the *log*(RT) "diff" vs. "same" trials: $t(19) = -0.26$, $p = 0.79$). **(C, D)** The distractor effect on choice and RT was not influenced by the Gabor orientations (two-sided *t*-test on the distractor effect on choice: $t(19) = 0.1$, $p = 0.92$, and the distractor effect on RT: $t(19) = 0.3$, $p = 0.74$). The error bars indicate SEM across participants, and the dots are individual participants.

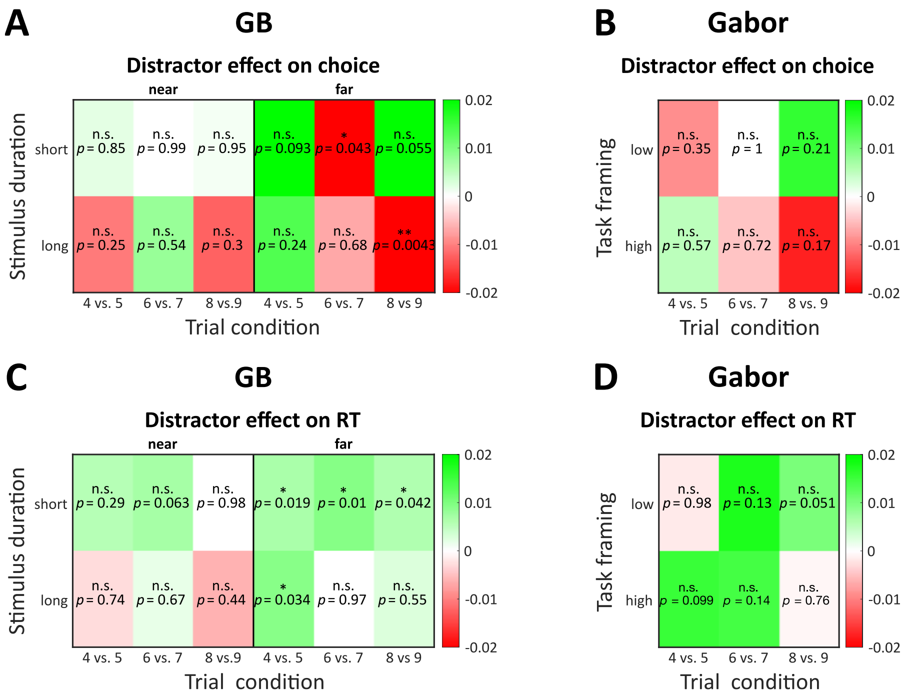

Figure S4. Distractor effect on choice and RT separately for each trial condition. The trial conditions were depicted in Figure 1B. In all panels the red shades indicate the negative distractor effect and green shades show the positive effects. The *p*_values are the result of two-sided one-sample *t*-tests on the distractor effect against zero.

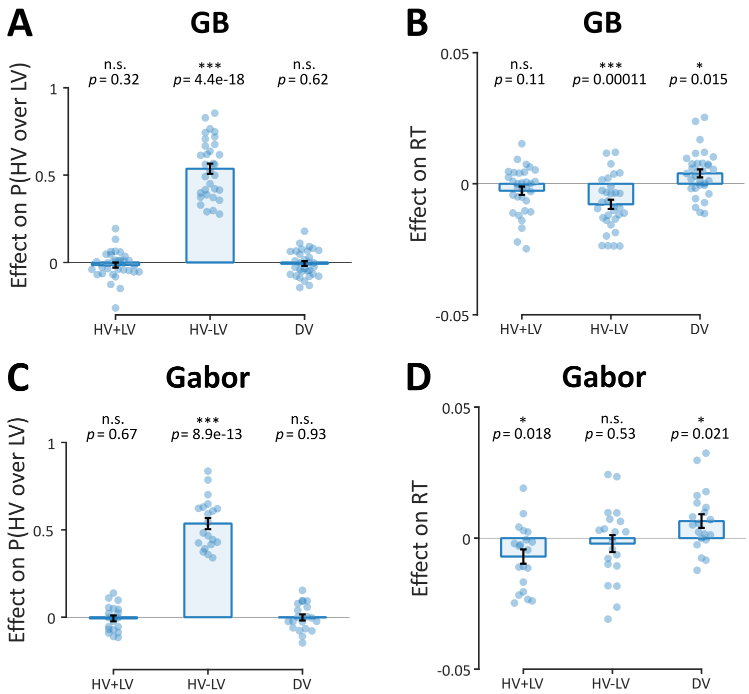

Figure S5. Distractor effect on choice and RT, regression analysis. (A, C) Beta coefficients of each regressor (in the x axis) indicates its effect on *P(HV over LV).* **(B, D)** The influence of each regressor on RT. Error bars in both panels are SEM across participants, and the dots show the individual participants. The *p*_values are the result of two-sided one-sample *t*-tests on the beta coefficients against zero.

Table S1. Dynamic models, best-fitted parameters**.**

Model / Parameter	DNRB +race	DNSI+race	DN +ffi
k	2.12±0.49	0.57±0.06	4.14±0.18
θ	1.71±0.1	1.71±0.1	1.58±0.08
I0	1.73±0.53	3.42±0.19	1.08±0.17
T_{nd}	0.05±0.01	0.05±0.01	0.05±0.01
c	-	-	0.72±0.02
σ^2	1	1	1
nc	1	-	-
β	8.26±1.97	0.29±0.02	-
β, softmax noise in race	0.19±0.02	0.29±0.02	-
w	0.1±0	0.11±0.01	0.11±0.01

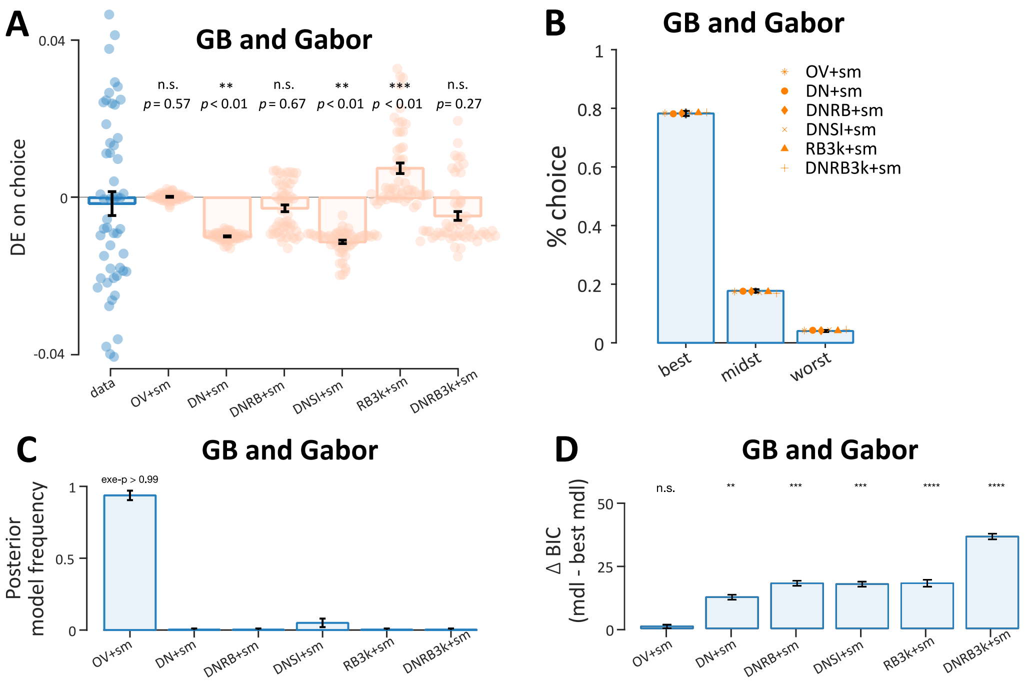

Figure S6. Static models. (A) Distractor effect on choice, a comparison between the actual data and simulated data using the best-fitted parameters. The *p*_values are the result of two-sided one-sample *t*-tests on the distractor effect in each model against the actual data. **(B)** The simulated probability choice of each alternative superimposed on the actual data, simulated by the best-fitted parameters of each model. **(C)** Random-effect Bayesian model comparison (Daunizeau et al., 2014; Rigoux et al., 2014). **(D)** Fixed-effect Bayesian model comparison, Black asterisks: significant ΔBIC against 10, one-sided one-sample *t*-tests (Kass & Raftery, 1995). In all panels, the error bars are SEM across participants.

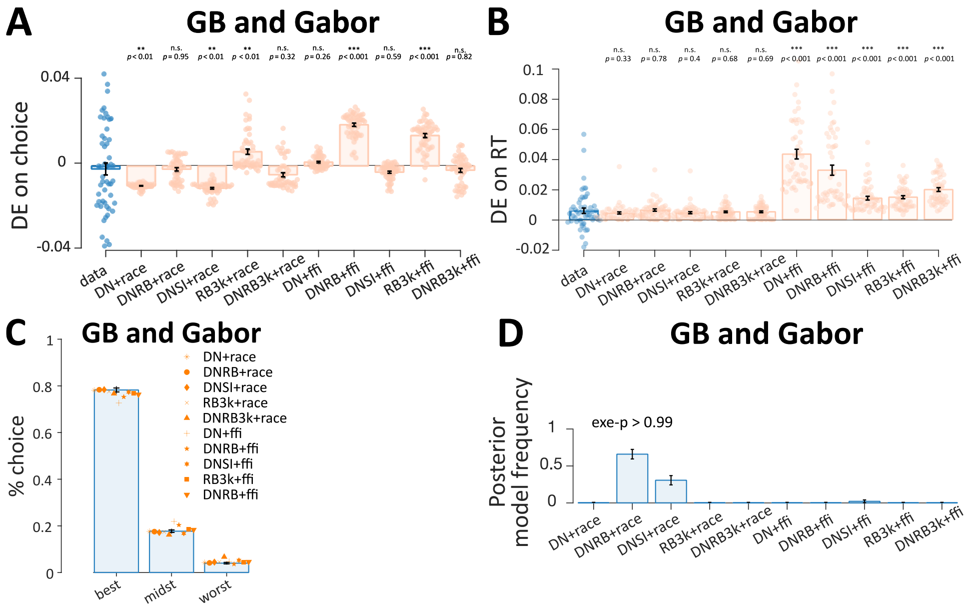

Figure S7. Dynamic models. (A, B) Distractor effect on choice and RT, a comparison between the actual data and simulated data using the best-fitted parameters. The *p*_values are the result of two-sided one-sample *t*-tests on the distractor effect in each model against the actual data. **(C)** The simulated probability choice of each alternative superimposed on the actual data, simulated by the best-fitted parameters of each model. **(D)** Random-effect Bayesian model comparison (Daunizeau et al., 2014; Rigoux et al., 2014). In all panels, the error bars are SEM across participants.

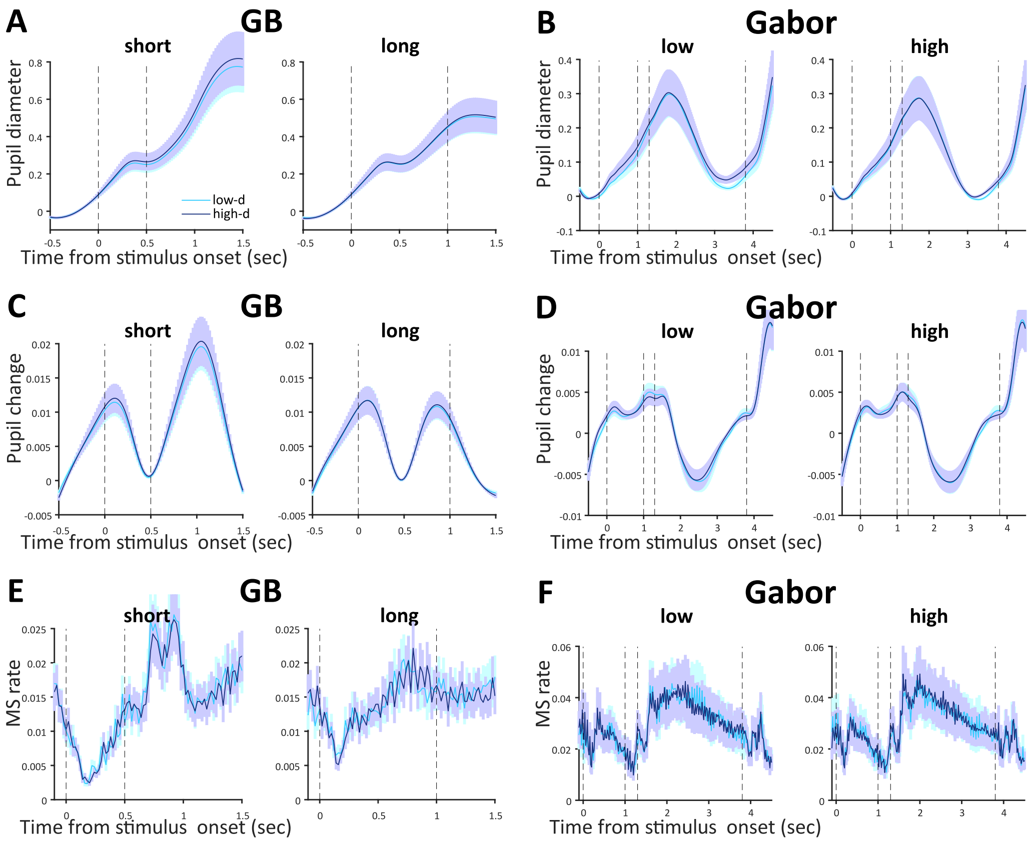

Figure S8. Pupil data across the trial. (A, B) The average pupil diameter. **(C, D)** The temporal derivative of pupil defined as pupil change. **(E, F)** The average microsaccade rate. In all panels, the thick lines indicate the average and the shaded areas are the SEM across participants. In "GB" panels, vertical dashed lines indicate the stimulus onset and offset. In "Gabor" panels, vertical dashed lines indicate the stimulus onset, framing cue, decision phase, and stimulus offset (from left to right).

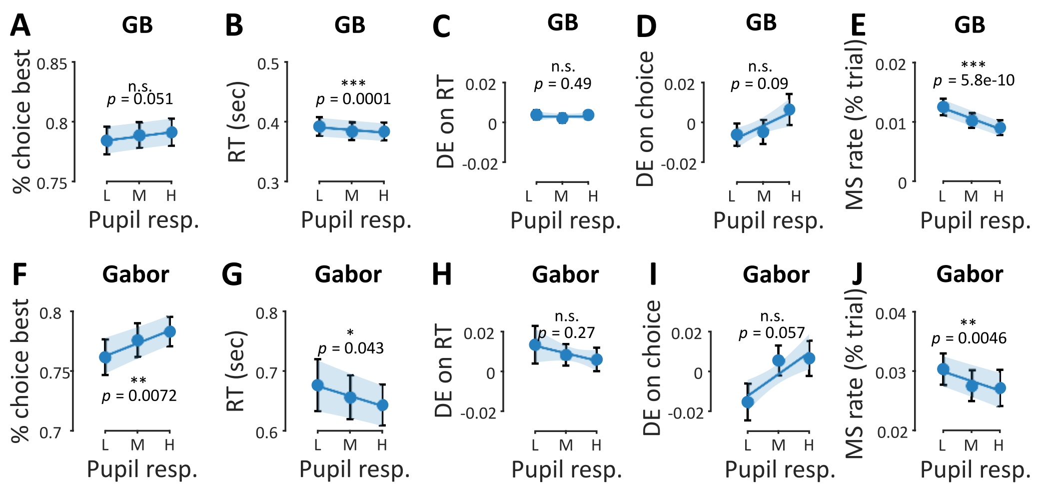

Figure S9. Pupil-linked arousal for each experiment during the decision window. Here, the analyses are equivalent to Figure 6 separately for each experiment. In all panels, the error bars indicate the SEM across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants. The *p*_values are the result of one-sided one-sample *t*-tests on the slope of the fitted lines against zero. The data is also pooled across two experiments.

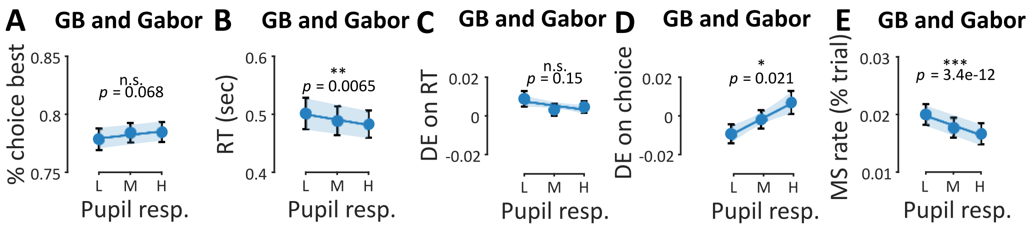

Figure S10. Pupil-linked arousal during the whole stimulus presentation. (A) Choice probability of the best alternative as the function of pupil response. **(B)** RT as the function of pupil response. **(C)** Distractor effect on RT as the function of pupil response. **(D)** Distractor effect on choice as the function of pupil response. **(E)** The relation between microsaccade rate and arousal. In all panels, the error bars indicate the SEM across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants. The *p*_values are the result of one-sided one-sample *t*-tests on the slope of the fitted lines against zero. The data is also pooled across two experiments.

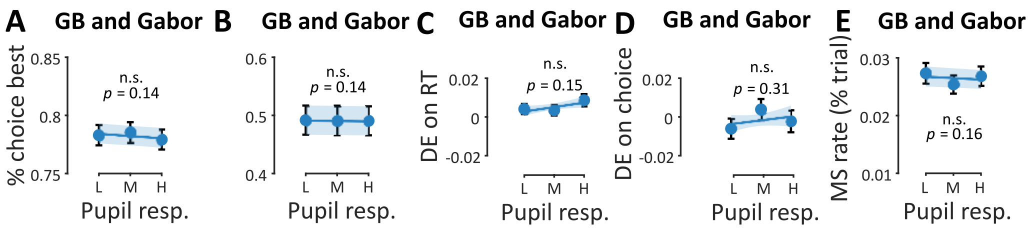

Figure S11. Tonic pupil-linked arousal. (A) Choice probability of the best alternative as the function of pupil response. **(B)** RT as the function of pupil response. **(C)** Distractor effect on RT as the function of pupil response. **(D)** Distractor effect on choice as the function of pupil response. **(E)** The relation between microsaccade rate and arousal. In all panels, the error bars indicate the SEM across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants. The *p*_values are the result of one-sided one-sample *t*-tests on the slope of the fitted lines against zero. The data is also pooled across two experiments.

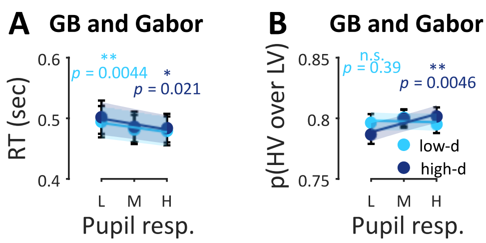

Figure S12. Pupil-linked arousal during the decision-making window for each low and high-distractor context. (A) RT as the function of pupil response. **(B)** Relative choice of HV over LV as the function of pupil response. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants. The *p*_values are the result of one-sided one-sample *t*-tests on the slope of the fitted lines against zero. Here the data is also pooled across two experiments.

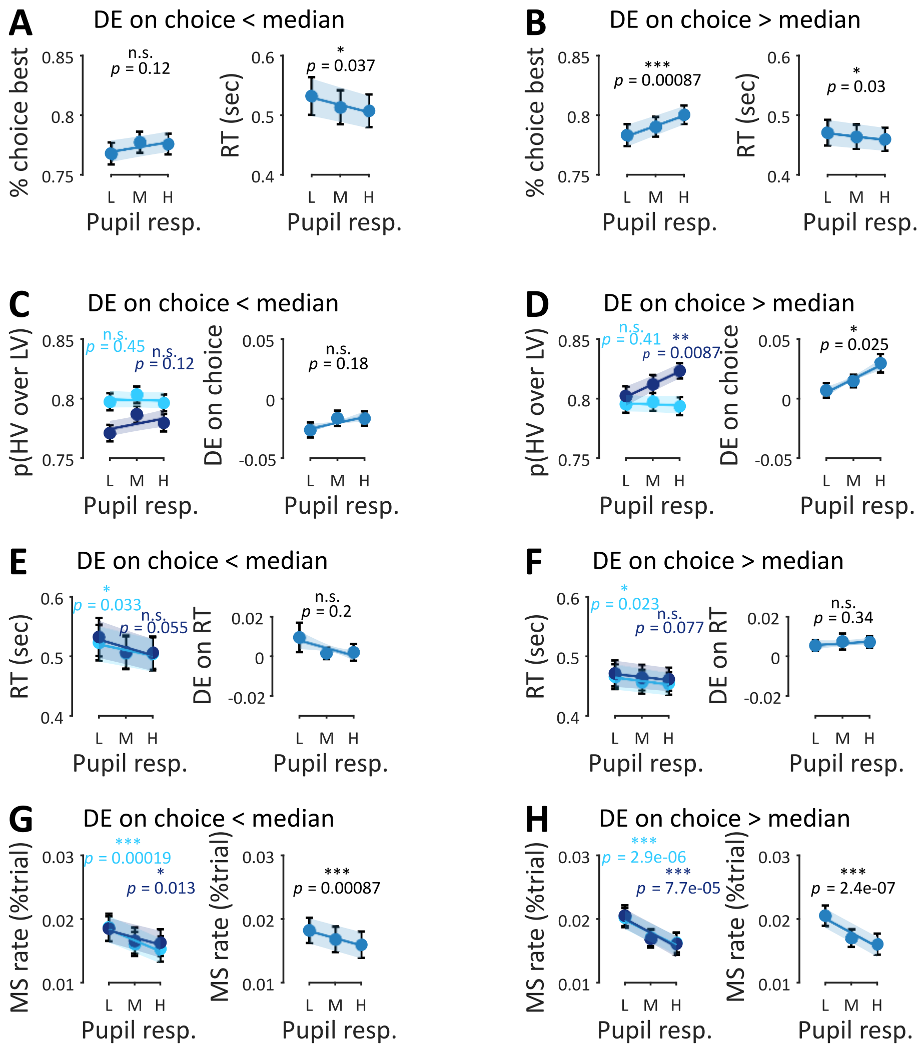

Figure S13. Pupil-linked arousal, median split. Here, the analyses and the data are equivalent to Figure 6 and S12, but plotted separately for two groups of participants based on a median split on the overall dictator effect on choice. In all panels, the error bars indicate the SEM across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants. The *p*_values are the result of one-sided one-sample *t*-tests on the slope of the fitted lines against zero. The data is also pooled across two experiments.

4 | Context effects in multi-attribute multi-alternative perceptual decisions

Summary

The "contextual preference reversal" phenomenon is a well-known form of immediate context effect in multi-alternative, multi-attribute decision-making. Decades of research have demonstrated that the addition of a third alternative with a specific configuration to a choice set can influence or even reverse preferences between the other two alternatives, a phenomenon known as "contextual preference reversal" (CPR) or the "decoy effect." The three classic decoy effects—attraction, similarity, and compromise—have primarily been observed in value-based decisions. Later, various value-based tasks have been used to replicate them, and limited research on perceptual decisions has been conducted. However, the robustness, interconnectedness, and fundamental processes of these context effects are still being debated. In this chapter, we designed a novel task with distinct perceptual attributes that incorporated all the key trials producing these classic biases. We successfully replicated the effects of attraction and compromise, but not similarity, in the realm of perceptual decisions. Then, we reported that attraction and compromise are positively correlated with each other, but negatively correlated with similarity. The design of this task using perceptual stimuli facilitated precise measurement of pupil responses. Thus, this allowed us to examine the role of global arousal in the underlying mechanisms of these complex contextual effects through the lens of pupil response. Interestingly, the overall context biases can be amplified when the level of arousal is higher.

Introduction

Do we prefer to buy organic (Bio) products at higher prices, or do we lean towards non-organic products at lower prices? To make almost every daily decision, we need to evaluate each alternative by weighing various attributes and combining them into a single utility. Investigating the mechanisms underlying evaluation in multi-attribute decisions is a significant focus in the behavioral sciences, particularly when multiple alternatives exist in the choice set. Experimental studies have revealed that when humans make multi-attribute, multi-alternative decisions they often change their preferences for the two most preferred alternatives when a less desirable alternative is introduced (Allingham & Allingham, 2002; Spektor et al., 2021; J. S. Trueblood et al., 2013; Tsetsos et al., 2010; Tsetsos, Chater, et al., 2012; Tversky, 1969; Tversky & Kahneman, 1981). For example, a preference for A (e.g., a costly Bio product) over B (e.g., an economical non-Bio product) can irrationally shift when a third inferior alternative (the decoy) C (e.g., an over-priced non-Bio product) is added to the choice-set (Huber et al., 1982b). Thus, contrary to normative theories, which postulate that there should be a fixed mapping between each alternative and its final utility independent of the other alternatives (Luce, 1959), preferences are influenced by the relative comparison among the available alternatives within the choice set, resulting in context effects. Attraction, similarity, and compromise effects have been proposed as three main classic context effects (Spektor et al., 2021) (see Figure 5 in the first chapter for a visual representation of these effects).

Up to date, numerous experimental and computational findings have tried to explain the mechanisms underlying these context effects using concepts like directing attention (J. Trueblood et al., 2022; J. S. Trueblood et al., 2014; Tsetsos, Chater, et al., 2012) and selective integration (Hotaling et al., 2010; Usher et al., 2019), normalization theories (Landry & Webb, 2021; Soltani et al., 2012), decision by sampling (Bhui & Gershman, 2018a; Noguchi & Stewart, 2014, 2018b), and other explanations (Bhatia, 2013; Dumbalska et al., 2020; Li et al., 2018; Natenzon, 2019; Rigoli, 2019). However, there is a lack of consensus regarding the underlying mechanisms and information processes that shape these context effects (Spektor et al., 2021). Understanding the mechanisms behind complex cognitive processes requires the experimental control of the input feeding into the process. In this study, we used new perceptual stimuli instead of economic alternatives to control the sensory input completely. Additionally, unlike previous studies that examined these effects in separate experiments, we included all key trials producing three classic context effects in a unified experiment to study their interrelatedness. Recently, it has been suggested that not all decoy effects are observed in the same participants when the experiment is designed to replicate these classic effects in the same individuals (Berkowitsch, Scheibehenne, & Richardson, 2014; Trueblood, Brown, & Heathcote, 2015). We also reported significant attraction and compromise effects, but did not observe a similarity effect. We then found a significant positive correlation between attraction and compromise, and a negative correlation between similarity and both.

Previous studies have mainly used gaze data to infer the roles of overt attention and information processing in context effects (Callaway et al., 2021; Noguchi & Stewart, 2014). Here, we aimed to precisely measure the pupil response, which serves as an indicator of the arousal system (De Gee et al., 2020; Nuiten et al., 2025; Urai et al., 2017). It has been shown that there is a causal and/or correlational relationship between tonic and phasic arousal and simple decision biases in sensory detection tasks (de Gee et al., 2017; De Gee et al., 2020; Nuiten et al., 2025; Urai et al., 2017). Therefore, we speculated that the arousal system might also influence the information processing involved in shaping these more complex decision-making biases. Our results reveal that global phasic arousal during decision-making impacts the strength of overall context biases. Taken together, these findings provide new insights into the contextual nature of complex decisions and would be a new benchmark for computational modeling.

Results

Task description and basic performance

Thirty-six healthy human participants performed a “gem-collector” task in three experimental sessions with three pharmacological manipulations (Lorazepam (LZP), Donepezil (DNP), and Placebo (PLC), see Materials and Methods). They were asked to collect the most valuable gems to maximize their total monetary reward obtained at the end of the task. Each gem value was characterized by two attributes, “uniqueness” and “purity” (i.e., gain and loss). We used two perceptual features, the length of a spiral and a set of dots, to associate them with the gem attributes resulting in two possible mappings between the attributes and the perceptual features. We randomized these two mappings as a between-subject factor. Thus, for half of the participants, the “uniqueness” and “purity” of the gem were represented by the length of a spiral and a set of dots respectively: longer spiral → higher value gem; and more dots → lower value gem. For the other half were the other around: more dots → higher value gem; and longer spiral → lower value gem. In each session, participants completed the main "gem-collector" task (Figure 1), which included 12 blocks, each with 82 trials. To study the three context effects (attraction, similarity and compromise), we included specific choice sets called "key" trials (see Figure 6 in Materials and Methods), in which there was no single correct answer, as both the "target" and "competitor" alternatives were equally valuable. To verify that the participants understood the task and were not making random choices, we also included "filler" trials with a clearly defined correct answer.

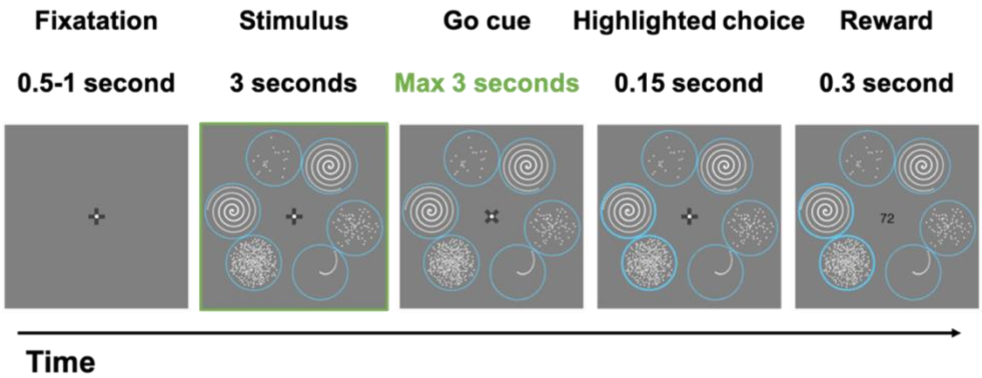

Figure 1. Experimental design. Each trial was initiated with the presentation of a fixation cue for a random time. Participants were instructed to maintain fixation on the cue throughout the entire trial. Then, the stimuli were presented on the screen for 3 seconds. After that, the fixation point rotated 45 degrees, signaling the go cue. Participants then had a maximum of 3 seconds to report their preferred alternative, after which their choice was highlighted for 0.15 seconds. The highlighted choice was then followed by its associated reward, which was displayed for 0.3 seconds.

To ensure that the participants followed the instructions of the task, which is choosing the alternative with the highest value, we first analyzed the “filler” trials. Figure 2A shows that participants chose the highest-value alternative significantly above chance levels of 33.3% in all three sessions (one-sample one-sided t-test against chance level in LZP: $t(35) = 47.92$, $p << 0.001$; PLC: $t(35) = 59.61$, $p << 0.001$; DNP: $t(35) = 52.32$,

p << 0.001). There was no difference in choice probability between the placebo and drug sessions (one-sample two-sided t-test between PLC and LZP: $t(35) = -1.65$, $p = 0.11$; PLC and DNP: $t(35) = 0.63$, $p = 0.53$). However, participants responded more slowly in the LZP session (Figure 2B, one-sample two-sided t-test on log(RT) between PLC and LZP: $t(35) = 3.21$, $p < 0.05$; PLC and DNP: $t(35) = -0.21$, $p = 0.83$), which can be due to lorazepam-induced cognitive slowing (Preston et al., 1988). For further analyses, we pooled data across these three sessions given that there was no difference in choice performance (1-way ANOVA on the choice probability of the best option in "filler" trials: $F(2,105) = 1.03$, $p = 0.36$) and the focus of this chapter is not to study the drug effects on the context effects. Figure 2C shows that the choice probability of each alternative in "filler" trials was thus consistent with value-guided decision-making.

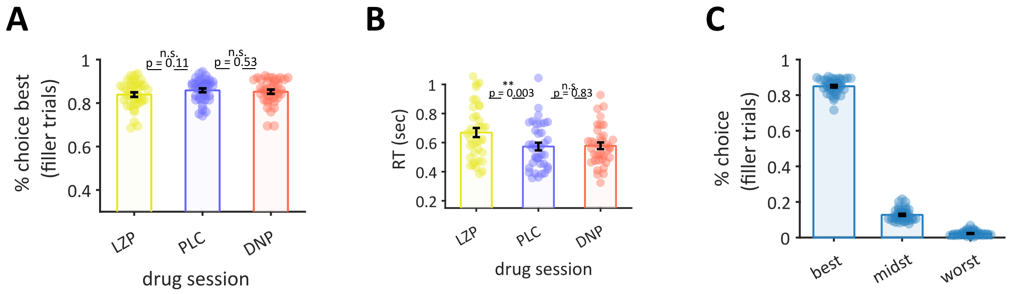

Figure 2. Basic Performance. (A) Choice probability of the best alternative in "filler" trials for each drug session. **(B)** Reaction time in all ternary trials (both "filler" and "key") for each drug session. **(C)** Choice probability of each alternative, "best", "midst", and "worst", in "filler" trials; data is pooled across three sessions. In all panels, the error bars indicate SEM across participants, and the dots are individual participants.

Replication of classic context effects and their interrelatedness

After ensuring that the participants followed the instructions for the task, we analyzed the "key" trials to investigate the presence of the three context effects within this novel task paradigm. We quantified each context effect by calculating the "relative choice share of the target" (RST) (Equation 1). Figure 3A shows that the attraction and compromise effects were significant, but the similarity effect was not (two-sided t-test against zero for attraction $t(35) = 7.79$, p << 0.001, compromise: $t(35) = 4.27$, p << 0.001, and similarity: $t(35) = -0.86$, p = 0.39). These results suggest that the attraction and compromise effects are more robust than the similarity effect. This finding is consistent with other reports (Dumbalska et al., 2020; Spektor et al., 2021). Recent reports also indicate that not all context effects are consistently observed in the same individuals when experiments are designed to elicit two or more of these effects simultaneously (J. S. Trueblood et al., 2015; Yang & Krajbich, 2023). It has been reported that the attraction and compromise effects are highly correlated and that they are anti-correlated with the similarity effect. To assess this claim, we calculated the correlation between these effects (Figure 3B), and the result was consistent with the previous reports. The data were pooled across all sessions because there was no interaction among the context effects across the sessions (N-way ANOVA on the context effects, drug session: $F(2, 315) = 0.23$, $p = 0.80$, effect: $F(2, 315) = 36.85$, $p << 0.001$, interaction: $F(4\ 315) = 2.1$, $p = 0.08$, check Figure S1 in the Extended Data for each session).

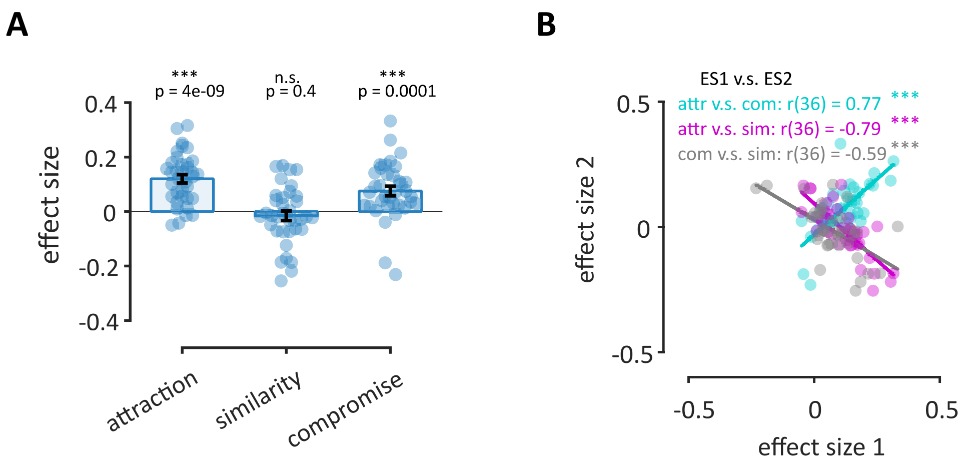

Figure 3. Context effects and their interrelatedness. (A) Context effects; there are significant attraction and compromise effects, but a lack of similarity effect. **(B)** Interaction between context effects; attraction and compromise are highly correlated and anti-correlated with the similarity effect. In panel A, the error bars indicate SEM across participants. In both panels, the dots represent individual participants. In panel B, the lines represent the fitted correlation lines.

The impact of phasic arousal on the strength of context effects

Studies have shown that fluctuations in arousal levels affect cognitive functions, including decision-making. Recent findings suggest that simple decision biases driven by sensory input in binary detection tasks are linearly related to phasic arousal state (De Gee et al., 2020; Nuiten et al., 2025; Urai et al., 2017). Based on these findings, we propose that arousal states may influence the broader decision biases even driven by spatial contextual features. Given our previous results in the previous chapter showing that elevated arousal is linked to enhanced performance (reflected in faster reaction times and higher accuracy) and a positive linear relationship between arousal and distractor effects, we investigated whether and how phasic arousal influences the strength or direction of the classic context effects. First, due to the pharmacological manipulation in this study, the tonic (500 milliseconds of baseline pupil dilation before stimulus onset) and phasic (1 second after stimulus onset and 2 seconds before the go cue) arousal during the sensory and decision windows were compared between all drug sessions. See the Materials and Methods section and Figure S2 in the Extended Data for further details showing pupil dilation across the trial. Figure 4 shows that there are no differences between drug sessions in the tonic and two phasic arousal windows (1-way ANOVA on the tonic arousal in Figure 4A: $F(2, 105) = 0.01$, $p = 0.99$; on the phasic arousal during sensory window in Figure 4B: $F(2, 105) = 0.22$, $p = 0.80$; and on the phasic arousal during the decision-making window in Figure 4C: $F(2, 105) = 0.08$, $p = 0.92$).

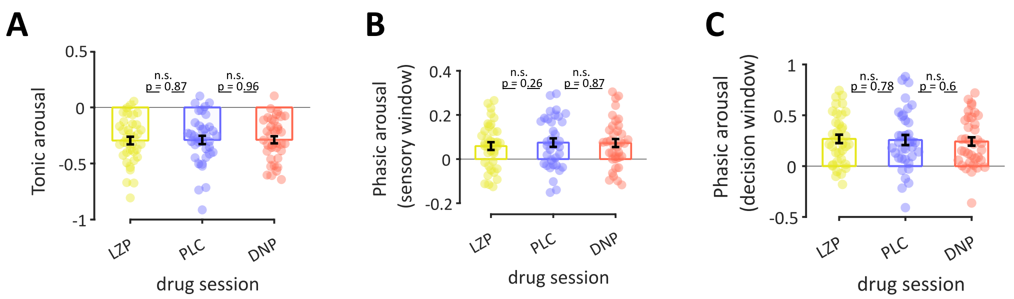

Figure 4. Tonic and phasic arousal across drug sessions and for different time windows. (A) Average pupil response across 500 milliseconds before stimulus onset, defined as tonic arousal. **(B)** Average pupil response during 1-second after stimulus onset, defined as phasic arousal during the sensory window. **(C)** Average pupil response during 2-second before go cue defined as phasic arousal during decision window. See the Materials and Methods section for more information. In all panels, the error bars indicate the standard error of the mean (SEM) across participants, and the dots represent individual participants. The *p*-values are the result of two-sided, one-sample t-tests between the drug and placebo sessions.

Since there was no difference in the tonic and phasic arousal between the drug sessions, and interpreting the detailed effects of the drug is beyond the scope of this chapter, we pooled the data from all three sessions for further analysis. To investigate the influence of phasic arousal on overall context biases, we focused on the decision-making window, assuming that information sampling and evaluation occur during this time. Figures 5A and 5B first show that participants performed faster as arousal increased; however, the accuracy did not significantly improve in the "filler" trials (one-sample, one-sided *t*-test on the beta coefficient of p_b in Equation 3 for the probability of choice in Figure 5A: $t(35) = 0.98$, $p = 0.17$; and for reaction time in Figure 5B: $t(35) = -3.59$, $p << 0.001$). Figure 5C illustrates that higher phasic arousal during the decision period results in higher overall context biases (one-sample, one-sided *t*-test on the beta coefficient of *p_b* in Equation 3 in Figure 5C: $t(35) = 2.07$, $p < 0.05$). Due to the interrelatedness of the context effects shown in the previous section, we calculated an overall context bias instead of analyzing each effect separately. To do so, we performed a principal component analysis (PCA) to determine the relative weight of each context effect. Then, we calculated the overall bias by summing each weight multiplied by its associated effect.

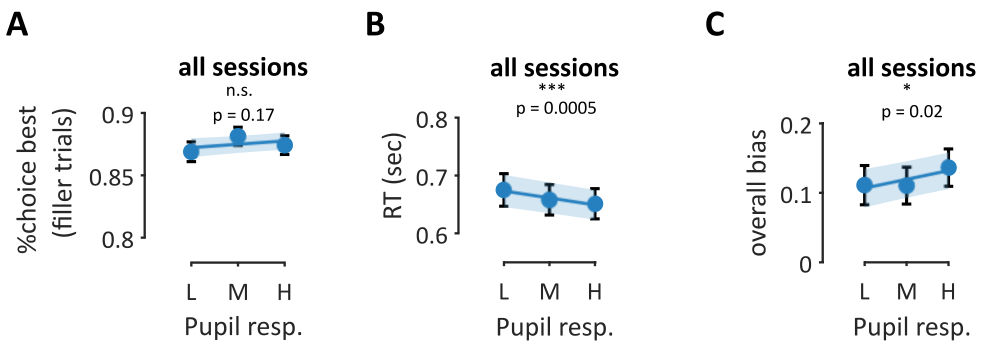

Figure 5. The influence of phasic arousal during decision time on context biases. The relationship between the phasic arousal and **(A)** the choice probability of the best alternative in "filler" trials, **(B)** reaction time in all ternary trials (both "filler" and "key"), **(C)** and overall context biases. In all panels, the error bars indicate the standard error of the mean (SEM) across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants.

Discussion

Decades of behavioral research have focused on elucidating preference reversal in multi-attribute, multi-alternative choices. Studies have shown that preferences can shift depending on how the alternatives are presented relative to each other (Allingham & Allingham, 2002; Spektor et al., 2021; J. S. Trueblood et al., 2013; Tsetsos, Chater, et al., 2012; Tsetsos et al., 2010; Tversky, 1969; Tversky & Kahneman, 1981). Several context effects, which arise from the specific spatial arrangement of the choice set, have been discovered in value-based decision-making (Busemeyer et al., 2019; Huber et al., 1982b; Simonson, 1989; Spektor et al., 2021; Tversky, 1972). For instance, presenting an inferior alternative (i.e., a decoy) similar to a superior alternative (i.e., a target) can make the target more appealing. This well-known attraction effect is one of the classic context effects (Huber et al., 1982b). Other observed context effects include compromise and similarity (Simonson, 1989; Tversky, 1972). They suggest that our decision-making process is not always based on fixed rules, but rather, can be fragilely influenced by external and internal factors (Luce, 1959, 1977). Many theories have tried to explain this fluctuation in behavior, but due to its complexity, there is still no clear consensus (Busemeyer et al., 2019; Spektor et al., 2021). In this study, we employed well-controlled perceptual stimuli with distinct attributes, including all three context effects, within a single experiment. We also introduced a new method of analyzing pupil responses to better understand the impact of internal and external factors on context effects.

First, we replicated three classic context effects in a new decision-making task with perceptual stimuli. One key finding was the robustness of the attraction and compromise effects compared to the similarity effect. Attraction and compromise biases were significantly observed in human choice behavior, but the similarity effect did not reliably emerge. These results are consistent with previous studies (Dumbalska et al., 2020; Spektor et al., 2021) that have suggested the similarity effect may be less stable or more susceptible to task-specific factors. Integrating all three classic context effects (attraction, similarity, and compromise) into a unified experimental paradigm provided further insight into their interrelatedness and potential underlying mechanisms. The positive correlation observed between the attraction and compromise effects and their negative correlation with the similarity effect further supports the view that these context effects may be partially dissociable in terms of their underlying cognitive processes or internal representational mechanisms (J. S. Trueblood et al., 2015; Yang & Krajbich, 2023), which may vary between individuals. Here, we investigated this important finding using linear correlation; however, we suggest that further investigation could be conducted using other methods in conjunction with computational modeling, such as cluster analysis. This method could group individuals who show all, some, or none of the context effects. Then, computational modeling could be used to distinguish the driving mechanisms of these effects in each group of individuals.

While previous research has primarily focused on attentional allocation (e.g., gaze tracking) to explain context effects, this chapter introduces the innovative use of pupillometry. This approach enabled us to examine the role of arousal as an internal factor that modulates decision biases (Nuiten et al., 2025). Our results indicate that higher levels of phasic arousal during decision-making are linearly associated with increased overall context bias. Previously, it has been proposed that arousal specifically enhances the representation of task-relevant variables (Aston-Jones & Cohen, 2005; Mather et al., 2016). Moreover, research on context effects suggests that increasing the representational precision can enhance the context effects (Spektor et al., 2021). This finding suggests that arousal plays a complementary role in the decision-making process by strengthening the internal representation of the stimuli. Alternatively, increased arousal may shift the decision-making process toward more optimal evaluations. This interpretation can be in line with previous findings proposing that irrationality is optimal during the noisy decision-making process (Tsetsos et al., 2016). All in all, these findings shed new light on the interplay between arousal as an internal cognitive state and contextual factors as an external modulation of choice. We would encourage future computational modeling to incorporate arousal as a dynamic variable modulating choice behavior, rather than treating it as noise or a secondary influence.

Notably, despite the pharmacological manipulations involving donepezil and lorazepam, no significant differences in context effects were observed at the behavioral level across drug sessions. While lorazepam significantly slowed reaction times, consistent with its known cognitive effects (Preston et al., 1988), without impairing task performance. These results suggest that the mechanisms contributing to context biases may be stable across varying baseline neurochemical states. However, complementary neural analyses are still necessary to reveal the neuromodulatory contributions to the decision-making process.

In summary, this study replicates classic findings on context-dependent preference reversals by demonstrating that such effects are also observable in controlled perceptual decision-making paradigms with an interrelatedness between them. We also demonstrated that internal arousal can impact decision-making and amplify context-driven biases. These findings pave the way for future computational models of decision-making that consider the influence of contextual factor and physiological state on human preferences.

Materials and Methods

Task and Datasets

The data presented in this chapter were pooled from two datasets collected in two different laboratories. The first 12 participants completed the task in a behavioral laboratory, where only pupillometry was measured. The next 24 participants completed the task in a magnetoencephalography (MEG) laboratory, where both pupillometry and MEG signals were recorded simultaneously. Due to the pharmacological intervention of the study, the task was completed in three different sessions. Since this chapter focuses on interpreting behavioral and pupillometry data from these two datasets, the following describes how the behavioral task and pupillometry were conducted. Additionally, since the task and its administration were identical in both laboratories, the data were pooled across the two datasets.

Participants and Procedure

Thirty-six participants (19 female and 17 male, aged 20–40) were recruited from the internal participant pool at the Institute of Neurophysiology and Pathophysiology at the University Medical Center Hamburg-Eppendorf. All participants gave written informed consent before starting the experiment. The study was approved by the local ethics committee of the Hamburg Medical Association. All participants had normal or corrected-to-normal vision and were right-handed. Each experimental session lasted between 5.5 and 6 hours and was divided into two parts. The first 3 hours consisted of taking the pills and waiting, followed by the behavioral task, which took ~2.5 to 3 hours. The behavioral task included 12 blocks (8-10 minutes each), and participants were allowed to take short breaks (< 1 minute) between blocks and one or two longer breaks (5-10 minutes) upon request. Participants received €110 for their participation (an hourly net rate of €20) in each session and a maximum of €40 for their task performance. Additionally, we paid a €200 completion bonus to encourage participants to attend all three sessions. The study involved a pharmacological intervention, and there was a minimum gap of seven days between each of the three sessions. All of the participants except one completed all three sessions. Here, we only included data from the 36 participants who completed all three sessions.

Main task

The task was implemented using Psychophysics-3 Toolbox in Matlab (The MathWorks Inc., 2022) on a 21” monitor with a screen resolution of 1920 x 1080 pixels and a refresh rate of 60 Hz. The stimuli were presented on a grey background [127.5 127.5 127.5] in a dimly lit room, with participants seated 60 cm away from the monitor. Participants completed a three-alternative, two-attribute perceptual decision-making task broken into 12 blocks of 82 trials. We gamified the task by instructing participants that each alternative represented a gem with two attributes: "purity" and "uniqueness." As "gem-collectors," their task was to collect the most valuable gems to maximize their total monetary reward at the end of the task. Two perceptual features were used to associate the gem attributes "purity" and "uniqueness" or "loss" and "gain": the length of a spiral and a set of dots. This resulted in two possible mappings between the attributes and the perceptual features. We randomized these two mappings as a between-subjects factor. Thus, for half of the participants, the "uniqueness" and purity" of the gem were represented by the length of a spiral and a set of dots, respectively (Figure 6A). The longer the spiral, the more unique and valuable the gem; more dots were associated with lower purity and lower value. For the other half, the "uniqueness" and purity" of the gem were represented by a set of dots and the length of a spiral, respectively (Figure 6B). More dots were associated with the more unique and valuable the gem, and a longer spiral was associated with lower purity and lower value. To ensure the mapping was clear, all participants completed a training block with only binary trials, choosing between alternatives with a single attribute. Then, they began the main task (Figure 1A), which included 12 blocks, each with 82 trials. To study the three context effects, we included ternary "key" trials, which resulted in classic context effects (Figure 6). For each choice set, there were 36 trials across all 12 blocks (e.g., 36 trials for choice set {A, B, ca}). In these "key" trials, there was no single correct answer because the "target" and "competitor" alternatives were both equally valuable. To ensure the participants understood the task and were not choosing randomly, we included a total of 100 "filler" ternary trials, each with one correct answer. We also included different combinations of binary pairs of alternatives from the design matrix in Figure 6 (e.g., {A, AY}). However, we did not analyze them here, as that was not the main focus of this chapter.

Each trial began with the presentation of a fixation cue after a random short delay drawn from a truncated exponential distribution. [0.5, 1], with a mean of 0.75 seconds. Then, the stimuli appeared on the screen, equidistant from the fixation cue at the top, left, and right. To mitigate bias toward the top stimulus, the entire array of stimuli was tilted either six degrees clockwise or counterclockwise. This tilt was randomized and counterbalanced between participants. The eccentricity was set to 2.2 visual degrees. The presentation of the stimuli lasted 3 seconds, which was immediately followed by a response window lasting up to 3 seconds. The response window was cued by a 45° rotation of the central fixation, prompting participants to report their choice by pressing a button. Their choice was then highlighted for 0.15 seconds, followed by the presentation of the collected reward for the chosen option at the center of the screen for 0.3 seconds. The response window had a maximum duration of 3 seconds. Failure to respond within this timeframe triggered an immediate "Missed Response" message on the screen. Responding earlier than this timeframe, during the stimulus presentation, was signaled by "Too Fast." These trials were terminated and repeated at the end of the block.

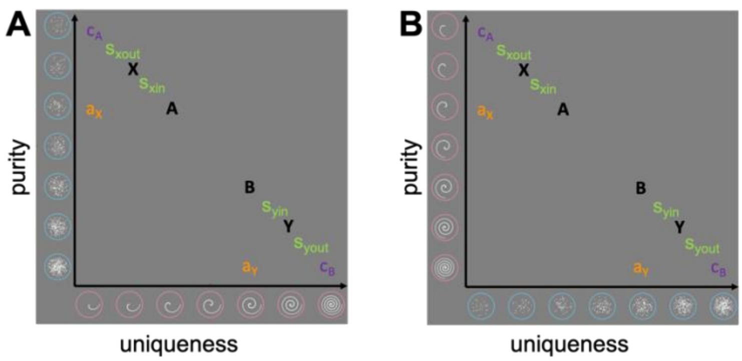

Figure 6. The design matrix of "key trials". (A) The "uniqueness" is represented by the length of spiral in x axis, and "purity" by the set of dots in y axis. **(B)** The "uniqueness" is represented by the set of dots in x axis, and "purity" by the length of spiral in y axis. In both panels, A and B are the target/competitor options and c_A,c_B the decoys for compromise effect. X and Y are the target/competitor options for attraction and similarity effects. The decoys for attraction effect are a_x and a_y and for similarity are s_{xout}, s_{xin}, s_{yout} and s_{yin}.

Pharmacological manipulation

Each participant completed three experimental sessions, in which they took lorazepam (1 mg), donepezil (5 mg), and placebo drugs. In each session, two identical-looking pills were administered as follows: LZP session (pill 1 = PLC, pill 2 = LZP); DNP session (pill 1 =

DNP, pill 2 = PLC); and PLC session (pill 1 = PLC, pill 2 = PLC). Due to the different times at which DNP and LZP reach peak plasma levels in the blood, and to ensure blinding to the pharmacological condition, two pills were administered in each session at different times before the behavioral task. The first pill was administered ~3 hours before the beginning of the behavioral task (according to the peak plasma level for DNP) (Rogers & Friedhoff, 1998), and the second pill was administered ~1.5 hours before the beginning of the behavioral task (according to the peak plasma level for LZP) (Greenblatt et al., 1982). We used a randomized, double-blind, within-subject, and crossover design, and the order of the drugs across sessions was counterbalanced between participants. We allowed at least a 7-day gap between consecutive sessions to allow plasma levels to return to baseline. Participants were observed the entire time, and their blood pressure and heart rate were measured every 30 minutes from the initial intake until the start of the behavioral task.

Behavioral Analyses

Relative choice share (RST)**:** To quantify the context effect we used the "relative choice share of the target (*RST*) (Berkowitsch et al., 2014; J. Trueblood et al., 2022)" metric. The relative choice share quantifies the choice share of the target (T) and competitor (C) alternatives relative to each other:

$$RST = \frac{P(T)}{P(T) + P(C)} \tag{1}$$

where *p(T)* and *p(C)* indicate the choice probability of the target and competitor alternatives in ternary trials (when the decoy option was available). A standard context effect occurs when *RST* > 0.5. So, we computed the effect size as:

$$Effect\ Size\ (ES) = RST - 0.5 \tag{2}$$

Thus, *ES* > 0 indicates the occurrence of a context effect.

Pupillometry

Pre-processing: We tracked pupil dilation, horizontal and vertical gaze positions at a sampling rate of 1000 Hz using an EyeLink 1000 (*SR Research Ltd.*, n.d.) in both behavioral and MEG laboratories. The eye-tracker was calibrated at the beginning of each block. For preprocessing the pupil time series within each block, we used custom-made Matlab scripts (Urai et al., 2017). Missing data points resulting from blinks and saccades, as detected by the EyeLink software, were interpolated from -150 ms to 150 ms around the missing data. Subsequently, the effect of blinks and saccades on the pupil response was estimated through deconvolution and removed from the data using linear regression (Knapen et al., 2016). The residual pupil time series were then band-pass filtered using a third-order Butterworth filter with cut-off frequencies of 0.01 to 6 Hz, z-scored per block of trials, and down-sampled to 50 Hz. To capture changes in pupil diameter, we computed the first temporal derivative of pupil diameter by subtracting adjacent frames and applied a low-pass filter with a cut-off frequency of 2 Hz (De Gee et al., 2020).

We included all trials from all participants in the analyses reported in this chapter.

Pupil response: To analyze the pupil response in each trial, the trials were epoched and baseline correction was performed by subtracting the mean pupil diameter from 500 milliseconds before stimulus onset. The average pupil diameter during the decision-making window was calculated and referred to as the pupil response for the arousal analysis. The decision-making window was defined as 2 seconds before the go cue. We also analyzed the data considering the sensory window (1-second after stimulus onset) and the entire stimulus presentation. The results are shown in Figures S3 and S4 in the Extended Data.

Arousal analysis: To investigate the influence of arousal on behavior, we looked the the corresponding behavior metric as the function pupil response. To achieve so, we first binned the average pupil response into three bins, then we used the following linear regression approach to quantify the influence of pupil response on the corresponding behavior metric:

$$y \sim \beta_0 + \beta_1 pb, \tag{3}$$

where *pb* is the bin number, we estimated the beta coefficients for each participant using the *polyfit* function in MATLAB.

According to Gee et al.'s definitions of phasic and tonic arousal (Nuiten et al., 2025), the focus of this chapter is the influence of phasic arousal on context effects during decision-making. However, due to the pharmacological manipulation in this study, the impact of tonic arousal was also examined. Tonic arousal is defined as the mean pupil response 500 milliseconds before stimulus onset. Figure S5 in the Extended Data shows that tonic arousal does not modulate overall context biases.

Acknowledgments

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Extended Data

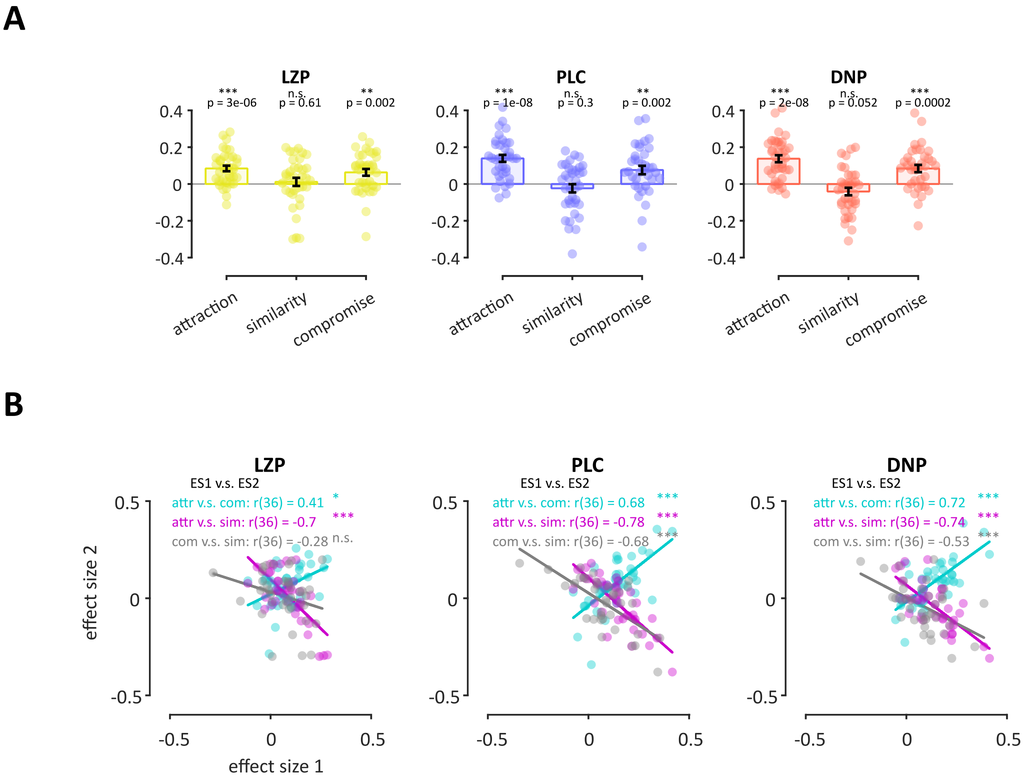

Figure S1. Context effects and their interrelatedness for each drug session. (A) Context effects, there are significant attraction and compromise effects, but no similarity effects, across each session. There was no interaction or difference among the context effects across the sessions (N-way ANOVA on the context effects, drug session: $F(2, 315) = 0.23$, $p = 0.80$, effect: $F(2, 315) = 36.85$, $p << 0.001$, interaction: $F(4, 315) = 2.1$, $p = 0.08$). However, the attraction effect is smaller in the LZP session than in the PLC and DNP sessions (two-sided t-test on the attraction effect in LZP vs. PLC: $t(35) = -3.28$, $p < 0.01$; and LZP vs. DNP: $t(35) = -3.82$, $p << 0.001$). **(B)** Interaction between context effects for each session. In panel A, the error bars indicate SEM across participants. In both panels, the dots represent individual participants. In panel B, the lines represent the fitted correlation lines.

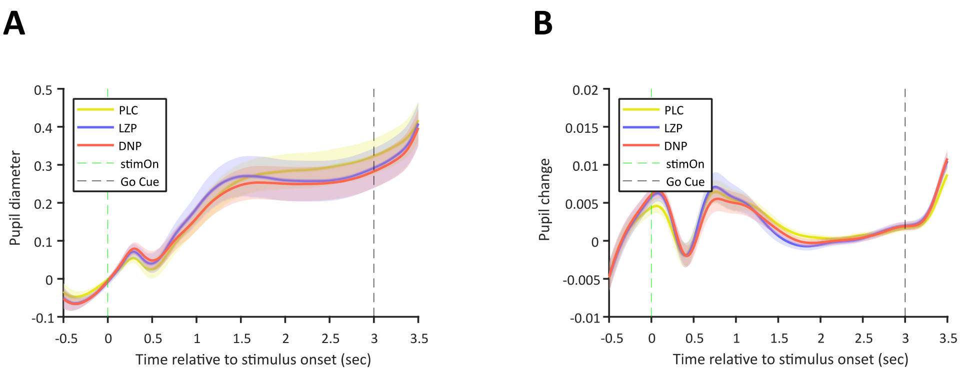

Figure S2. Pupil data across the trial for each drug session. (A) The average pupil diameter. **(B)** The temporal derivative of pupil defined as pupil change.

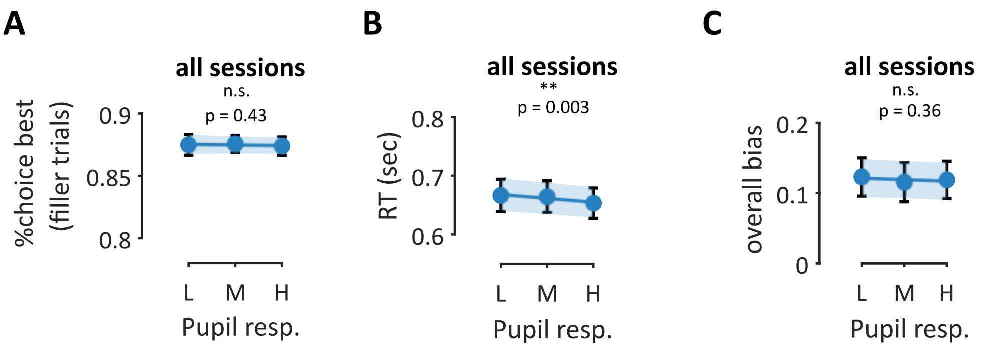

Figure S3. The influence of phasic arousal during sensory time on context biases. The relationship between the phasic arousal and **(A)** the choice probability of the best alternative in "filler" trials, **(B)** reaction time in all ternary trials (both "filler" and "key"), **(C)** and overall context biases. In all panels, the error bars indicate the standard error of the mean (SEM) across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants.

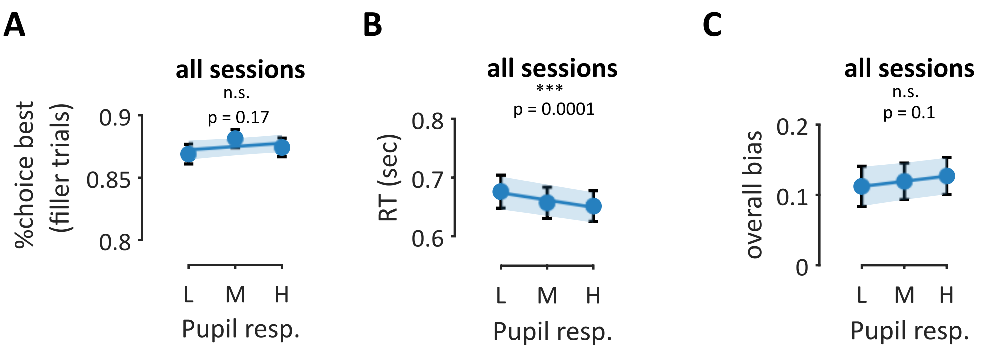

Figure S4. The influence of phasic arousal during the whole stimulus duration on context biases. The relationship between the phasic arousal and **(A)** the choice probability of the best alternative in "filler" trials, **(B)** reaction time in all ternary trials (both "filler" and "key"), **(C)** and overall context biases. In all panels, the error bars indicate the standard error of the mean (SEM) across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants.

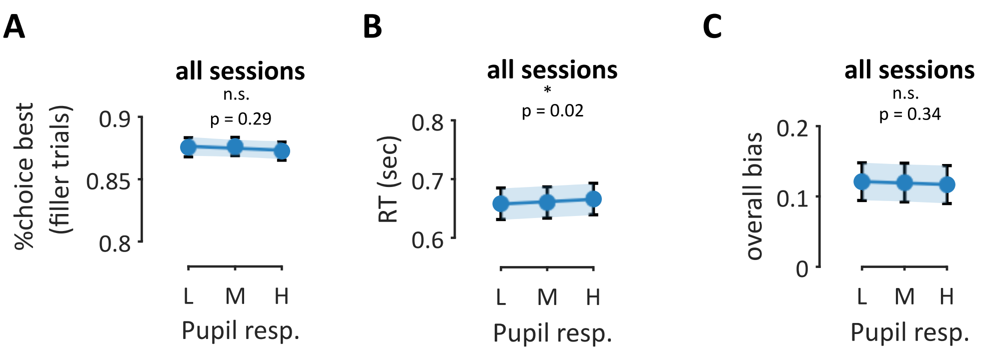

Figure S5. The influence of tonic arousal on context biases. The relationship between the tonic arousal and **(A)** the choice probability of the best alternative in "filler" trials, **(B)** reaction time in all ternary trials (both "filler" and "key"), **(C)** and overall context biases. In all panels, the error bars indicate the standard error of the mean (SEM) across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants.

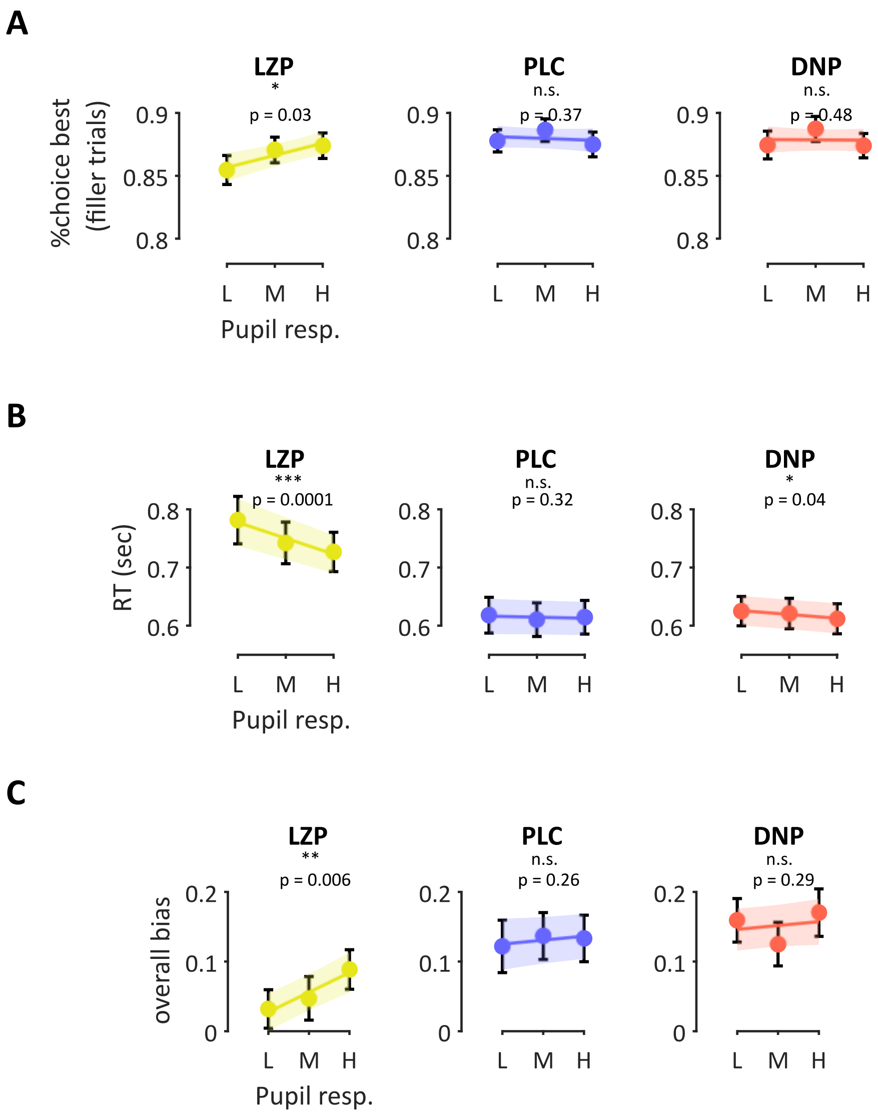

Figure S6. The influence of phasic arousal during decision time on context biases for each session. The relationship between the phasic arousal and **(A)** the choice probability of the best alternative in "filler" trials, **(B)** reaction time in all ternary trials (both "filler" and "key"), **(C)** and overall context biases. In all panels, the error bars indicate the standard error of the mean (SEM) across participants. The lines are the averages of the linear fits to the data, and the shaded areas are the SEMs across participants.

5 | Discussion

Summary

Scholars in psychology, neuroscience, and behavioral economics have long been challenged by the question of how humans make decisions among multiple alternatives. One particularly intriguing phenomenon is the set of context effects, in which the presence or characteristics of an irrelevant alternative - often known as "*distractor*" or "*decoy*”- systematically biases preferences. The context effects challenge the *Independence of Irrelevant Alternatives (IIA)* axiom of rational choice theory by suggesting that preferences are not fixed, but rather, are constructed dynamically based on contextual features such as the composition of the choice-set. Despite decades of research, the exact mechanisms behind context effects remain unclear, due to their complexity and the variability of findings across studies. In this thesis, we designed well-trackable value-learning experiments to investigate the role of temporal vs. immediate contexts in the formation of distractor effects. Using perceptual stimuli rather than value-based options enabled us to investigate the generalizability and robustness of context effects further. We then employed computational modeling and a new arousal-based analysis to explain the underlying mechanisms and the influence of brain states on context effects, respectively. This discussion aims to synthesize these findings, explore potential explanations for the observed phenomena, and pave the way for future research.

Introduction

Decision-making, one of the fundamental cognitive processes that should be based on logical reasoning, is not immune to systematic biases. *Preference reversal* is one of such biases that arises when individuals face multiple alternatives with various attributes (Rieskamp et al., 2006; Tsetsos et al., 2010; Tversky, 1969; Tversky & Kahneman, 1981). For instance, if someone is following a healthy diet, they should consistently prefer the healthier snack (e.g., a banana over a chocolate bar) after exercising. However, when a third option (e.g., a muffin) is available, they may end up choosing the chocolate bar over the banana. This is an example of a *preference reversal,* known as the attraction effect (Huber et al., 1982a), which falls under the broader category of multi-attribute context effects (Spektor et al., 2021). This example highlights that alternatives are usually evaluated in relative terms rather than in isolation. Context effects like the attraction effect violate the *independence of irrelevant alternatives (IIA)* principle, an axiom of choice theory (Luce, 1959, 1977), and suggest that decisions are not necessarily made by adhering to fixed, rational rules. Decades of theoretical and experimental research have sought to uncover the underlying mechanisms of context effects (Busemeyer et al., 2019; Spektor et al., 2021). Proposed explanations have ranged from relative value coding (Louie et al., 2013; Shen et al., 2025; Soltani et al., 2012) to sampling from memory (Bhui & Gershman, 2018b; Noguchi & Stewart, 2014; Tohidi-Moghaddam & Tsetsos, 2025) and selective information sampling (Tsetsos, Chater, et al., 2012). Yet, due to the complexity of this problem and the fragility and variability of the context effects across experimental settings, a full understanding remains puzzling. Thus, in this thesis, we employed the following techniques to solve a small piece of this puzzle:

1- We employed well-controlled designs to determine the role of immediate vs. temporal contexts in context-dependent behavior (**Chapter 2**). More importantly, using perceptual stimuli allowed me to investigate the replicability and robustness of these biases, from simple context effects (i.e., the "*distractor effect*") in uni-attribute choice problems (**Chapters 2 and 3**) to multi-attribute ones (i.e., the "*decoy effect*" in **Chapter 4**).

2- We then used an extended version of the decision-by-sampling model, which is based on a memory-based binary comparison, to explain how temporal context distorts value representation during learning, which consequently shapes the *distractor effect* on choice (**Chapter 2**). To explain the absence of *distractor effect* on choice in an immediate context but its footprint of the reaction time, we then used a multi-level model (**Chapter 3**). This model includes normalization coding and binary comparison at the evaluation stage and then a race model to complete the final action.

3- Lastly, we used a novel method of analysis to explore the influence of arousal on the *distractor effect* (**Chapter 3**) and *decoy effects* (**Chapter 4**), to shed light on the way brain state shapes context effects.

Synthesis of Results

Chapter 2 disentangles the role of immediate and temporal context in shaping choices. Immediate context refers to the available alternatives at the moment of choice, and temporal context refers to the influence of alternatives encountered over time (Louie & De Martino, 2014). Previous studies have reported either a positive or a negative distractor effect on the choice (Chau et al., 2020; Itthipuripat et al., 2015, 2019; Louie et al., 2013). This effect has been interpreted as the influence of immediate context. However, in a couple of these studies, decision-making occurred either in parallel with or after a learning phase (Itthipuripat et al., 2015, 2019). In other studies, different contexts were interleaved within experimental blocks (Bavard & Palminteri, 2023). Consequently, temporal context may have also contributed to the observed effects. To dissociate the influence of immediate and temporal contexts, we designed a value-learning task involving three alternatives within each context. In each mini-block, participants first learned the value of the three alternatives associated with that context. Then, they reported their learned subjective values before making a series of binary and ternary decisions. Measuring the learned subjective values was a key element of our design. First, it allowed us to examine whether the observed distractor effect emerged solely at the time of choice (immediate context) or during learning through value distortion (temporal context). Second, measuring the learned subjective values provided critical insight into the underlying mechanism necessary for developing a computational model. We did not observe an overall distractor effect during the decision phase. However, the reported subjective values indicated that value distortion occurred during the learning phase. Additionally, we observed individual variability of distractor effects (i.e., both positive and negative) across participants, which were correlated with the value distortion during learning. Our results suggest that in a value-learning task, the distractor alternatives influence value representations over longer timescales (i.e., temporal context) rather than exerting an immediate influence at the choice moment (i.e., immediate context). The direction and between-person variability of this distortion cannot be explained by existing normalization models. To address this issue, we proposed a stochastic, rank-based model inspired by the decision-by-sampling theory. This model accounts for the observed value distortion and the range of distractor effects across participants.

Chapter 3 first investigates the replicability and generalizability of the observed distractor effect in perceptual decision-making tasks. Secondly, it examines the validity of the existing divisive normalization theory, which has been proposed as a general mechanism for context-dependent decision-making (Louie et al., 2011, 2013). Some studies have reported that a high-value distractor alternative reduces preference for the best alternative, which is known as the negative distractor effect (Itthipuripat et al., 2015; Louie et al., 2013). Others have reported a positive distractor effect, in which a higher-value distractor alternative in the choice set increases the preference for the best alternative (Bavard & Palminteri, 2023; Chau et al., 2020). However, these effects were not replicated in a previous study, while a slower reaction time was observed in the presence of a high-value distractor alternative (Gluth et al., 2020). To clarify these inconsistencies, we used a carefully designed perceptual task in which all value information was instantly available, thus avoiding learning or prior preferences effects. Our results showed no distractor effect on choice, but rather consistently longer decision times when a high-value distractor was present. Additionally, using pupil dilation as a proxy for phasic arousal, we observed a positive linear relationship between arousal and the direction of the distractor effect from negative to positive. Despite the perceptual nature of the task, these findings cannot be explained by divisive normalization theory alone. Instead, we interpreted these results using a two-stage framework. In the first stage, the valuation stage, low-level normalization processes suppress value signals by increasing the difference between the two best alternatives when a high-value distractor is present. However, binary comparisons based on the model proposed in Chapter 2 can distort the perceived value of alternatives by decreasing the difference between the two best alternatives, thereby boosting the value of the best alternative and counteracting the influence of divisive normalization. In the action stage, a race model based on the traditional drift-diffusion framework determines the final action. Thus, higher value suppression in the valuation stage results in a slower reach of the decision boundary by the race model. Using this framework, we also interpreted the relationship between arousal and the distractor effect. At lower levels of arousal, the evaluation stage is mainly modulated by low-level normalization encoding, resulting in a negative distractor effect. In contrast, higher arousal may represent higher-level cognitive processes, such as memory-based binary computations, which result in a positive distractor effect.

Chapter 4 assesses the generalizability, robustness, and interrelatedness of decoy effects in multi-alternative decision-making tasks utilizing distinct perceptual attributes. Decoy effects, which include attraction, compromise, and similarity, have been identified as systematic changes in choice behavior that depend on the specific choice-set compositions (Huber et al., 1982a; Simonson, 1989; Tversky, 1969). Decades of empirical and theoretical work have sought to explain this phenomenon, thereby enriching our understanding of decision-making more broadly (Dumbalska et al., 2020; Evangelidis et al., 2018; Hasan & Trueblood, 2024; Y. Liu & Trueblood, 2023; Spektor et al., 2021; J. S. Trueblood et al., 2013; J. S. Trueblood & Pettibone, 2017; Tsetsos, Chater, et al., 2012; Tsetsos et al., 2010). In this study, we used a new three-alternative decision-making task with two distinct perceptual attributes to examine the three classic decoy effects in one experimental design. This allowed us to examine the relationships between these effects. Overall, we observed robust attraction and compromise effects but not a similarity effect in this novel experiment. Notably, the attraction and compromise effects were positively correlated and negatively correlated with the similarity effect, suggesting that they can have partially distinct underlying cognitive mechanisms. We also introduced pupillometry to study the role of arousal, an internal state that may influence decision-making. Our results showed that higher phasic arousal during choice was linked to stronger overall context biases. These results suggest that arousal may play a role in the decision-making process. These findings can open new directions for computational models of decision-making that account for both external features of the choice context (i.e., specific choice-set compositions) and internal cognitive state factors.

Context Effects: from distractor to decoy effects

In multi-alternative decision-making, context effects have been the focus of extensive research (Busemeyer et al., 2019; Spektor et al., 2021). This is because the choice-set composition can alter the decision-making process and challenge traditional theories of rational choice. In this thesis, we examined context effects across the spectrum, from simple distractor effects (Chau et al., 2020; Itthipuripat et al., 2015; Louie et al., 2013) to complex decoy effects (Huber et al., 1982a; Y. Liu & Trueblood, 2023; Simonson, 1989; Spektor et al., 2021; J. S. Trueblood et al., 2013; Tversky, 1972), using controlled perceptual and value-learning tasks. We found that, although distractors did not reliably influence the ultimate choice, they distorted value learning over time and increased decision times in perceptual tasks. We also demonstrated individual variations in distractor effects. Using a novel task with perceptual stimuli, we replicated attraction and compromise effects, but not the similarity effect. Interestingly, we demonstrated the interrelatedness of decoy effects among individuals. This variability implies that these effects may not stem from a single, generalized context-processing system but rather from a combination of cognitive computations. These results further suggest that understanding individual differences is key to advancing our understanding of the contextual nature of choice.

Previous studies on context effects, particularly decoy effects, have primarily focused on specific compositions of choice sets in which all options are presented simultaneously at the moment of choice (i.e., immediate context) (Dumbalska et al., 2020; Evangelidis et al., 2018; Hasan & Trueblood, 2024; Y. Liu & Trueblood, 2023; Spektor et al., 2021; J. S. Trueblood et al., 2013; J. S. Trueblood & Pettibone, 2017;

Tsetsos, Chater, et al., 2012; Tsetsos et al., 2010). Limited research has examined how the temporal order of options affects decoy effects (i.e., temporal context) (Evans et al., 2021). However, based on the value-learning study findings in Chapter 2 (Tohidi-Moghaddam & Tsetsos, 2025), our arousal analysis, and previous findings, we propose that context effects may be driven not only by a specific configuration of options at the time of choice but also by temporal dynamics. We propose that further research incorporating explicit temporal manipulations could provide deeper insights into the origins of these effects. Furthermore, to directly examine how information is evaluated and integrated throughout the decision-making process, experimental tasks should be designed to allow for the step-by-step tracking of sampled information, similar to our initial value-learning task in Chapter 2. These tasks would allow researchers to monitor what participants learn about each option over time rather than inferring learning outcomes from final choices alone.

Role of Arousal and Internal States

Beyond experimental manipulation, such as contextual features, which are external factors influencing our choice behavior, examining internal cognitive states is also essential to fully understand the underlying mechanisms of context effects on choice. The arousal analysis performed in Chapters 3 and 4 showed that the context effects are not only modulated by external factors, but also the internal states play a complementary role to boost or hinder them. Previous research has also shown that arousal, as one of the internal state metrics, can impact the decision biases encountered in simple sensory tasks (de Gee et al., 2017; De Gee et al., 2020; Nuiten et al., 2025). Using computational modelling, they also clarified that pupil link arousal can influence the evidence accumulation process (i.e., the drift rate) (Urai et al., 2017). Thus, this deviation in behavior does not originate merely from external factors, but rather from internal dynamics; arousal-linked variations can influence the dynamics of decision-making from trial to trial. Over the past few years, there has been a trend toward the models capturing the full range of context effects between participants (Chau et al., 2020; Shen et al., 2025; Tohidi-Moghaddam & Tsetsos, 2025). However, according to these arousal findings, a model should be able to capture inter-trial variability even within a participant.

Previous studies on simple decision bias mainly used free-response paradigms (de Gee et al., 2017; De Gee et al., 2020; Nuiten et al., 2025; Urai et al., 2017). So, the decision-making time window was clearly defined as a 1-second response locked window. In our design, using a fixed-duration paradigm to define the decision-making time window was a confounding factor because decisions could be made earlier in long-duration tasks or later in short-duration tasks. Therefore, further studies are needed to examine the arousal effect using well-controlled designs for arousal analysis. Second, although pupil diameter is a useful proxy for arousal, it is still an indirect measure. Combining pupilometry with other direct measures of arousal, such as brain imaging, could provide a more comprehensive picture of how internal cognitive states influence contextual decision-making.

Most importantly, previous studies have shown that higher arousal reduces choice-induced biases in simple decision tasks (De Gee et al., 2020; Nuiten et al., 2025; Urai et al., 2017). However, our findings reveal the opposite trend: an increase in distractor effects and overall context effect biases under high arousal. One interpretation is that these might be fundamentally different types of biases. In binary decision tasks, which usually have clearly defined correct and incorrect responses, bias can be conceptualized as a deviation from the correct choice. In contrast, in complex, multi-alternative, and multi-attribute decision-making tasks, there is no objectively correct answer. Instead, bias manifests as shifts in choice preferences driven by contextual factors of the choice-set. Alternatively, both types of bias may share a common underlying mechanism that are modulated by arousal. It has been shown that higher arousal enhances the representation of task-relevant variables (Aston-Jones & Cohen, 2005; Mather et al., 2016). Under this framework, the reduction in bias in simple tasks may be due to improved focus on the correct, goal-relevant option. However, in complex tasks, it has been shown that stronger context effects, such as attraction and compromise effects, often arise under conditions associated with enhanced stimulus precision, longer presentation times, or higher concreteness of the stimuli (Spektor et al., 2021). These factors are associated with an increased representation of task-relevant features, which could amplify context-driven biases rather than reduce them.

Lastly, these new findings about arousal challenge the traditional dual-process theory of decision-making. According to this theory, there are two processing systems: System 1 is fast, intuitive, and automatic, while System 2 is slow, deliberate, and analytical (Kahneman, 2011; Rand et al., 2012). According to this framework, biased choices are usually attributed to System 1, while careful deliberation through System 2 is expected to mitigate such biases. However, pupil dilation analyses indicate that context-dependent biases are associated with greater cognitive effort under higher arousal, rather than reduced effort. Similarly, previous research has shown that context effects become stronger with longer deliberation times in free-response paradigms (Cataldo & Cohen, 2021; Dhar et al., 2000). These findings suggest that context effects may emerge or be amplified by extended analytical processes rather than being a byproduct of System 1. They also highlight the need to reconsider the dichotomy between fast/irrational and slow/rational processes.

In sum, these findings suggest that the impact of arousal on choice biases is not universally increasing or decreasing for all types of biases. Rather, it may influence shared cognitive processes involved in decision-making, which consequently shape that bias. This underscores the need for future studies to reveal a more nuanced understanding of how arousal interacts with task structure and cognitive processes. Such studies would shed light on how decision biases are shaped across domains and, more broadly, improve our understanding of decision-making.

Concluding remarks

In summary, our integrated set of studies demonstrates that context effects are not fixed biases of decision-making, but rather task- and state-dependent phenomena. These effects emerge from complex interactions between external choice alternatives, internal valuation systems, and physiological states. While previous theoretical explanations have often emphasized universal and directionally consistent biases such as those predicted by divisive normalization, our findings highlight the importance of individual differences and task-specific feature and internal cognitive states in shaping context effects. This suggests a need to shift from seeking a universal framework toward developing models that accommodate heterogeneity and flexibility in human decision-making. This also raises the question: should we aim for a unified framework that accounts for all context effects, or instead adopt a more liberal approach that embraces variability across individuals and tasks?

6 | General Summary

English

Decision-making is one of the most fundamental cognitive processes that is susceptible to systematic biases. Context effects are a well-known family of these biases, wherein the presence of an irrelevant alternative influences preferences. This irrelevant alternative is called a "*distractor*" in uni-attribute decisions and a "*decoy*" in multi-attribute decisions. These context effects suggest that preferences are not fixed but dynamically shaped by the composition of the choice set. Thus, they challenge the Independence of Irrelevant Alternatives (IIA) principle of rational choice theory, which states that preference between two high-value alternatives should remain intact, regardless of the presence of a third alternative. Despite decades of research, the mechanisms underlying context effects remain unclear, partly due to their complexity and inconsistent findings. This thesis addresses this issue via two approaches. First, we conducted carefully designed value-learning experiments to distinguish the roles of immediate vs. temporal contexts in shaping distractor effects. Second, we used perceptual rather than value-based stimuli to test the robustness and generalizability of context effects in uni- and multi-attribute decisions.

The contribution of immediate vs. temporal contexts on the emergence of the distractor effect has still been debated. To address this, we developed a value-learning paradigm in which participants first learned the value of three alternatives in each context, then reported their subjective value, and finally made binary and ternary choices. Crucially, subjective value reports allowed us to identify whether distractor effects emerged during the learning phase or at the moment of choice. Results revealed no consistent distractor effect in final choices; instead, value distortions appeared in subjective values during learning. Our findings suggest that during value-learning, the value of a distractor alternative distorts value representations over a long timescale spanning several learning and choice trials. Importantly, divisive and range normalization fail to capture the direction and across-participant variability of this distortion. Our data is best captured by a mechanism that constructs subjective value representations via a series of binary comparisons between pairs of alternatives in each context. These findings revealed new information about the timescale and computational mechanisms underlying context-dependent, uni-attribute, multi-alternative choices.

Next, we tested the replicability of these distractor effects in perceptual decision-making tasks where all value information was available at the moment of choice. This removed the influence of prior learning. Results from two different perceptual tasks showed no distractor effect on choice, but decision time was prolonged when a high-value distractor was present. Furthermore, analyses of pupil dilation revealed that internal arousal states modulate the direction of the distractor effect on choice. At low arousal, distractors tend to have negative effects. At high arousal, however, the effects of distractors shift toward positive. Current static, context-dependent models cannot intrinsically explain the distractor effect on reaction times. To explain these findings, we proposed a dynamic model that incorporates valuation and decision stages. The model uses a combination of normalization theory and binary comparison, which is based on decision-by-sampling theory, to calculate subjective value in the valuation stage. Normalization theory explains negative distractor effects, while binary comparison captures positive ones. Thus, the combination of these two strategies can account for the null distractor effect on choice. Next, the subjective value is fed into a race model, which ultimately determines reaction time (RT) and accounts for the distractor effect on RT. This framework can also explain arousal findings. The negative distractor effect in low-level arousal may result from the greater influence of normalization on value representation, while the positive distractor effect in higher arousal may result from greater binary comparisons. Overall, we concluded that distractor alternatives influence the decision-making process. This influence may affect either the ultimate choice, as reported in previous studies, or the response time.

Beyond distractor effects, we examined the robustness and relationships among classic decoy effects (attraction, compromise, and similarity) using a novel, three-alternative, perceptual task with distinct attributes. The results revealed strong attraction and compromise effects, but no consistent similarity effect. Notably, attraction and compromise were positively correlated, and both were negatively correlated with similarity. This suggests that they may have partly distinct underlying processes. Pupillometry again demonstrated that higher arousal strengthened overall context biases. Together, these findings highlight that decision-making depends on both external choice structures and internal physiological states (e.g., arousal state), the latter of which can amplify or redirect context effects. These findings open new directions for computational models that integrate contextual and physiological factors to better capture the variability of human decision-making.

Deutsch

Die Entscheidungsfindung ist einer der grundlegendsten kognitiven Prozesse, die systematischen Verzerrungen unterliegt. Kontexteffekte sind eine bekannte Gruppe dieser Verzerrungen, bei denen das Vorhandensein einer irrelevanten Alternative die Präferenzen beeinflusst. Diese irrelevante Alternative wird bei Entscheidungen mit einem einzigen Attribut als „*Distraktor*" und bei Entscheidungen mit mehreren Attributen als „*decoy*" bezeichnet. Diese Kontexteffekte deuten darauf hin, dass Präferenzen nicht feststehen, sondern dynamisch durch die Zusammensetzung der Auswahlmöglichkeiten geprägt werden. Damit stellen sie das Prinzip der Unabhängigkeit irrelevanter Alternativen (IIA) der rationalen Entscheidungstheorie in Frage, das besagt, dass Präferenzen zwischen zwei hochwertigen Alternativen unabhängig von einer dritten Alternative unverändert bleiben sollten. Trotz jahrzehntelanger Forschung sind die Mechanismen, die Kontexteffekten zugrunde liegen, nach wie vor unklar, was zum Teil auf ihre Komplexität und widersprüchliche Forschungsergebnisse zurückzuführen ist. Diese Arbeit befasst sich mit dieser Frage anhand von zwei Ansätzen. Zunächst führten wir sorgfältig konzipierte Experimente zum Wertelernen durch, um die Rolle des unmittelbaren und des zeitlichen Kontexts bei der Entstehung des Distraktor-Effekts zu unterscheiden. Zweitens verwendeten wir wahrnehmungsbasierte statt wertbasierter Reize, um die Robustheit und Generalisierbarkeit von Kontexteffekten bei Entscheidungen mit einem oder mehreren Attributen zu testen.

Der Beitrag von unmittelbaren gegenüber zeitlichen Kontexten zur Entstehung des Distraktor-Effekts ist nach wie vor umstritten. Um dieser Frage nachzugehen, haben wir ein Wert-Lern-Paradigma entwickelt, bei dem die Teilnehmer zunächst den Wert von drei Alternativen in jedem Kontext lernten, dann ihren subjektiven Wert angaben und schließlich binäre und ternäre Entscheidungen trafen. Entscheidend war, dass wir anhand der subjektiven Wertangaben feststellen konnten, ob Distraktor-Effekte während der Lernphase oder im Moment der Entscheidung auftraten. Die Ergebnisse zeigten keinen konsistenten Distraktor-Effekt bei den endgültigen Entscheidungen; stattdessen traten während des Lernens Wertverzerrungen in den subjektiven Werten auf. Unsere Ergebnisse deuten darauf hin, dass während des Wertlernens der Wert einer Distraktor-Alternative die Wertdarstellungen über einen langen Zeitraum hinweg verzerrt, der mehrere Lern- und Entscheidungsversuche umfasst. Wichtig ist, dass die Divisive- und Range-Normalisierung die Richtung und die Variabilität dieser Verzerrung zwischen den Teilnehmern nicht erfassen kann. Unsere Daten lassen sich am besten durch einen Mechanismus erfassen, der subjektive Wertdarstellungen über eine Reihe von binären Vergleichen zwischen alternativen Paaren in jedem Kontext konstruiert. Diese Ergebnisse lieferten neue Informationen über den Zeitrahmen und die Berechnungsmechanismen, die kontextabhängigen, einattributigen Entscheidungen mit mehreren Alternativen zugrunde liegen.

Als Nächstes haben wir die Reproduzierbarkeit dieses Distraktor-Effekts in Wahrnehmungsentscheidungsaufgaben getestet, bei denen alle Wertinformationen zum Zeitpunkt der Entscheidung verfügbar waren. Dadurch wurde der Einfluss des vorherigen Lernens ausgeschlossen. Die Ergebnisse aus zwei verschiedenen Wahrnehmungsaufgaben zeigten keinen Distraktor-Effekt bei der Entscheidung, aber die Entscheidungszeit verlängerte sich, wenn ein Distraktor mit hohem Wert vorhanden war. Darüber hinaus zeigten Analysen der Pupillenerweiterung, dass interne Erregungszustände die Richtung des Distraktor-Effekts bei der Entscheidung modulieren. Bei geringer Erregung haben Distraktoren tendenziell negative Auswirkungen. Bei hoher Erregung verschieben sich die Auswirkungen von Distraktoren jedoch in positiv Richtung. Aktuelle statische, kontextabhängige Modelle können den Distraktor-Effekt auf die Reaktionszeiten nicht intrinsisch erklären. Um diese Ergebnisse zu erklären, haben wir ein dynamisches Modell vorgeschlagen, das Bewertungs- und Entscheidungsphasen einbezieht. Das Modell verwendet eine Kombination aus Normalisierungstheorie und binärem Vergleich, die auf der Decision-by-Sampling-Theorie basiert, um den subjektiven Wert in der Bewertungsphase zu berechnen. Die Normalisierungstheorie erklärt negative Distraktor-Effekte, während der binäre Vergleich positive Effekte erfasst. Somit kann die Kombination dieser beiden Strategien den Null-Distraktor-Effekt bei der Entscheidung erklären. Als Nächstes wird der subjektive Wert in ein Race-Modell eingeführt, das letztendlich die Reaktionszeit (RT) bestimmt und den Distraktor-Effekt auf die RT berücksichtigt. Dieser Rahmen kann auch die Ergebnisse zur Erregung erklären. Der negative Distraktor-Effekt bei geringer Erregung kann aus dem größeren Einfluss der Normalisierung auf die Wertdarstellung resultieren, während der positive Distraktor-Effekt bei höherer Erregung aus stärkeren binären Vergleichen resultieren kann. Insgesamt kamen wir zu dem Schluss, dass Distraktoralternativen den Entscheidungsprozess beeinflussen. Dieser Einfluss kann sich entweder auf die endgültige Entscheidung auswirken, wie in früheren Studien berichtet, oder auf die Reaktionszeit.

Über die Distraktor-Effekte hinaus untersuchten wir die Robustheit und die Beziehungen zwischen klassischen Kontexteffekten (Attraction, Compromise und Similarity) anhand einer neuartigen Wahrnehmungsaufgabe mit drei Alternativen und unterschiedlichen Attributen. Die Ergebnisse zeigten starke Attraction- und Compromise-Effekte, jedoch keinen konsistenten Similarity-Effekt. Bemerkenswert ist, dass Attraction und Compromise untereinander positiv und beide mit Similarity negativ korrelierten. Dies deutet darauf hin, dass sie teilweise unterschiedliche zugrunde liegende Prozesse haben könnten. Die Pupillometrie zeigte erneut, dass eine höhere Erregung die allgemeinen Kontexteffekte verstärkt. Zusammengenommen unterstreichen diese Ergebnisse, dass die Entscheidungsfindung sowohl von externen Wahlstrukturen als auch von internen physiologischen Zuständen (z. B. Erregungszustand) abhängt, wobei letztere die Kontexteffekte verstärken oder umlenken können. Diese Ergebnisse eröffnen neue Wege für Computermodelle, die kontextuelle und physiologische Faktoren integrieren, um die Variabilität der menschlichen Entscheidungsfindung besser zu erfassen.

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9 Curriculum Vitae

Lebenslauf aus datenschutzrechtlichen Gründen nicht enthalten.

10 | Eidesstattliche Erklärung

Ich versichere ausdrücklich, dass ich die Arbeit selbständig und ohne fremde Hilfe, insbesondere ohne entgeltliche Hilfe von Vermittlungs- und Beratungsdiensten, verfasst, andere als die von mir angegebenen Quellen und Hilfsmittel nicht benutzt und die aus den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen einzeln nach Ausgabe (Auflage und Jahr des Erscheinens), Band und Seite des benutzten Werkes kenntlich gemacht habe. Das gilt insbesondere auch für alle Informationen aus Internetquellen.

Soweit beim Verfassen der Dissertation KI-basierte Tools („Chatbots“) verwendet wurden, versichere ich ausdrücklich, den daraus generierten Anteil deutlich kenntlich gemacht zu haben. Die „Stellungnahme des Präsidiums der Deutschen Forschungsgemeinschaft (DFG) zum Einfluss generativer Modelle für die Text- und Bilderstellung auf die Wissenschaften und das Förderhandeln der DFG“ aus September 2023 wurde dabei beachtet.

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Ich erkläre mich damit einverstanden, dass meine Dissertation vom Dekanat der Medizinischen Fakultät mit einer gängigen Software zur Erkennung von Plagiaten überprüft werden kann.

Maryam Tohidi-Moghaddam

Hamburg, September 2025