Hybrid Service Delivery

Purposeful Integration and Design of Artificial Intelligence for the Automation and Augmentation of Online Service Encounters

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Mathis Poser

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Evaluators:

First evaluator: Prof. Dr. Eva A. C. Bittner

Second evaluator: Prof. Dr. Tilo Böhmann

Third evaluator: Prof. Dr. Dominik Siemon

Abstract

Motivation

The adoption rate of artificial intelligence (AI) and its application for the automation or augmentation of tasks and activities in organizations is steadily increasing. With its potential to enhance value creation by elevating operational efficiency and productivity, AI can be implemented to create a competitive advantage. To leverage this potential for value creation and to address the heightened expectations of service seekers (SKs), organizations apply AI-based solutions for the delivery of online intangible services. Represented as virtual agents or integrated in user interfaces, AI can be used to meet SKs' needs for personalized, bidirectional, and chat-based interaction. By deploying conversational agents (CAs), which are provided with an identity and represented virtually, the availability, accessibility, and efficiency of text-based online service delivery can be increased by automating service encounters. In augmented service encounters, hybrid intelligence systems (HISs) can be used to combine the complementary capabilities of service employees (SEs) and AI, represented as a virtual agent, or integrated in a user interface, through collaboration. However, exploiting AI's potential to automate and/or augment cognitive activities in online service delivery is not a self-fulfilling endeavor. First, the automation of service encounters is associated with limitations, as the bounded capabilities of CAs can lead to service failure. Second, HISs need to be improved in regard to collaboration between AI and SEs to increase the effectiveness of augmented service encounters. Third, the automation and/or augmentation of service encounters requires the renewal of socio-technical constellations of AI, SK, and SE to ensure successful online service delivery. By adapting and complementing CAs and HISs, the goal of this dissertation is the development of knowledge for the creation of human-centered AI-based solutions that are represented as virtual agents or embedded in user interfaces to allow hybrid online service encounters. In doing so, integration points for service processes and tasks are determined and knowledge for the design of AI-based solutions is generated. This enables, on the one hand, the realization of hybrid consecutive online service encounters with handover of SK requests to SEs to avoid CA failure. On the other hand, AI-based virtual agents and user interfaces can be constructed to support SEs in hybrid simultaneous online service encounters.

Research Design

This cumulative dissertation follows the ground rules of the design science research (DSR) paradigm to pursue the research goal. The conducted research activities refer to nine publications that interconnect the three cycles of DSR and address six research questions. Motivated by the different epistemological interests in the context of defining the problem space and producing the solution space, several research methods have been applied in this cumulative dissertation. Literature reviews were conducted to capture existing scientific knowledge to identify research gaps and consider descriptive as well as prescriptive knowledge for the cumulative generation of knowledge contributions. The development of a taxonomy contributed to an improved understanding of the integration of AI-based solutions into online service delivery work systems. To generate the design knowledge, different qualitative methods were applied. Semi-structured interviews were conducted to identify real-world challenges as well as goodness criteria for solutions. In addition, interviews and focus groups were used for the evaluation of the design knowledge and its instantiation with prototypes. The collected data were examined by performing qualitative content analyses. Quantitative methods were applied to assess the influence of created design entities in the form of prototypes on individuals. The collected primary and secondary data were analyzed using different statistical methods.

Results

This cumulative dissertation presents validated knowledge for the human-centered design of AI-based solutions and their integration into work systems for the hybrid delivery of text-based online services. The results of the dissertation are divided into contributions with descriptive (Ω) and prescriptive (λ) character. The Ω-knowledge contributions, on the one hand, refer to the presentation of current operational challenges in online service delivery work systems. On the other hand, existing infusion archetypes are renewed to determine the constellations of AI, SK, and SE for online service encounters. The λ-knowledge contributions are presented in two forms. With a model, design principles, and instantiated design entities, design knowledge is presented that can be used to integrate and create AI-based solutions. As part of automated and/or augmented online service encounters, the resulting virtual agents or user interfaces can be applied for the hybrid delivery of text-based online service. In addition to this detailed design knowledge, design patterns are provided that aggregate the accumulated design knowledge by presenting four problem-solution pairs.

Contribution

The dissertation contributes to research on online service delivery, future of work, and human-AI interaction with validated knowledge for the design of human-centered AI-based solutions and their integration into work systems to enable hybrid, text-based online service delivery. In the context of online service delivery, the results of the dissertation help to overcome current drawbacks and leverage untapped potentials of automation and/or augmentation strategies for text-based online service. The presented design knowledge in the form of design principles and design patterns for the creation of AI-based solutions that are represented as virtual agents or embedded in user interfaces can be (re)used in research to create a synergy between automation and augmentation approaches by combining them. The interdependence of the two AI approaches can thereby be harnessed for the optimization of online service production. In the context of future of work research, the results of the dissertation confirm the suitability of adopting a socio-technical lens to redesign work processes and redistribute activities between AI and SEs while accounting for the emerging interdependencies between the social and technical subsystems. Furthermore, the results imply that the involvement of employees for the identification of value-creating deployment scenarios for AI can help to alleviate existing operational challenges and combine human and AI capabilities in a human-centered fashion. As an advancement of work practices in online service delivery work systems, the dissertation presents a handover approach for the dyadic delegation of activities between AI and SEs to enable different forms of hybrid collaboration. In the context of human-AI interaction research, the presented knowledge provides insights into the design of AI-based solutions to hybridize automated and augmented service encounters. In augmented service encounters, human-centered support of SEs can be achieved, if AI presents relevant information in a concise format at the appropriate time. By considering the dynamics of request processing that arises due to the synchronicity of the interaction with SKs, SEs can be adequately supported in processing information, making decisions, and solving problems. In automated service encounters, SKs can be supported by the structural guidance of AI-based solutions, in the form of CAs, in providing relevant information that facilitates SEs to continue request processing after it has been handed over to them.

The results of the dissertation also have implications for practice, as they can support organizations to integrate AI-based solutions into online service delivery work systems and design hybrid, text-based online service encounters as part of automation and/or augmentation strategies. By applying work analyses that account for arising interdependencies between the social and technical subsystems, organizations can determine useful deployment scenarios for AI. Furthermore, the taxonomy can be used to structure design decisions for the implementation of AI-based solutions. The presented prescriptive design knowledge can be used in organizations to adapt and complement existing CAs and/or HISs or create AI-based solutions to enable the hybrid delivery of text-based online service delivery. Organizations can thereby improve the robustness to failure in automated as well as collaboration between SEs and AI in augmented online service encounters.

Limitations

The cumulative dissertation is faced with a few limitations that concern the definition of the problem space, the production of the solution space, and the performed evaluation activities. By conceptualizing the problem space, real-world challenges and requirements for solutions were identified. The selection of companies and use cases threatens the generalizability of the discovered challenges that obstruct the delivery of online service in practice. To ensure a representative selection of companies and employees in two application contexts, established sampling methods were applied. To define the problem space, qualitative data have been used. Therefore, the results might have been influenced by researchers' interpretation of data. To mitigate this risk, established coding methods were used. In addition, multiple researchers were involved in the analysis of qualitative

data to reduce bias. In the production of the solution space, design knowledge was generated by considering existing scientific knowledge. The selection and neglect of existing literature has an impact on the definition of design knowledge. To mitigate this risk and achieve a contribution beyond existing scientific knowledge, established methods for the objective, valid, and reliable selection of literature were used. Further limitations refer to the evaluation of the produced design knowledge. Owing to the instantiation and evaluation of the design knowledge in a small number of companies in two application contexts, the projectability of the design knowledge is limited. Moreover, the validity of the results is restricted, as SKs were simulated in the semi-naturalistic evaluation settings. Furthermore, validation of the design patterns is limited to the evaluation of their components comprising design principles that are included in the publications.

Future Research

The dissertation provides several starting points for future research on the integration and design of AI-based solutions for online service delivery. In the context of studies about the integration of AI-based solutions into online service delivery work systems, the involvement of employees for determining the deployment scenario and characteristics of AI could be expanded by utilizing low-code development platforms. In addition, the perspective of SKs should be considered to a greater extent in defining requirements for AI-based solutions and their satisfaction with hybrid online service delivery should be evaluated. To generate insights into the advantages and disadvantages of their implementation, the effectiveness of hybrid online service delivery in the context of automation or augmentation approaches or their combination should be compared. Future research on the design of AI-based solutions for online service delivery should address the augmentation of service encounters in which AI is visible to SKs. In this context, AI's characteristics in regard to its behavior and representation should be determined. Furthermore, design knowledge should be produced for the development of solutions that enable additional forms of handovers between AI and SEs. As another aspect, the design of human-AI interaction in hybrid simultaneous online service encounters can be extended by adapting it to the needs of employees with different characteristics. With individual configurations in user interfaces of AI, customized support formats for employees with different experience levels could be produced.

Kurzfassung

Motivation

Die Adoptionsrate und Verbreitung von künstlicher Intelligenz (KI) für die Automatisierung oder Augmentierung von Aufgaben und Aktivitäten in Unternehmen nimmt stetig zu. Mit dem Potential die Wertschöpfung durch die Steigerung von Effizienz und Produktivität zu verbessern, wird KI für die Etablierung von Wettbewerbsvorteilen eingesetzt. Um diese Wertschöpfungspotentiale zu heben und die gestiegenen Erwartungen von Dienstleistungsempfängern zu erfüllen, setzen Unternehmen zunehmend KI-Lösungen für die Erbringung von immateriellen online Dienstleistungen ein. Repräsentiert als virtuelle Agenten oder integriert in Nutzeroberflächen, können mit KI die Bedürfnisse von Dienstleistungsempfängern nach personalisierter, bidirektionaler und chatbasierter Interaktion erfüllt werden. Mit dem Einsatz von konversationalen Agenten (KA), die mit einer Identität ausgestattet und virtuell repräsentiert werden, können die Erreichbarkeit, Zugänglichkeit und Effizienz von online Dienstleistungserbringung durch die automatisierte Beantwortung von Anfragen erhöht werden. Durch den Einsatz von hybriden Intelligenzsystemen (HIS) können die komplementären Fähigkeiten von menschlichen Dienstleistungserbringern und KI, repräsentiert als virtueller Agent oder integriert in eine Nutzeroberfläche, durch deren Kollaboration kombiniert werden. Durch diese Augmentierung kann die Effektivität der Dienstleistungsinteraktion erhöht und die kontinuierliche Weiterentwicklung der Fähigkeiten von KI sichergestellt werden. Das Ausschöpfen des Potenzials von KI für die Automatisierung und/oder Augmentierung von kognitiven Aktivitäten in der online Dienstleistungserbringung ist jedoch mit einigen Herausforderungen verbunden. Erstens ist die Automatisierung von Dienstleistungsinteraktionen mit KA durch deren begrenzte Fähigkeiten mit Fehlfunktionen verbunden. Zweitens besteht Weiterentwicklungsbedarf für HIS in der Herstellung hybrider Kollaboration zwischen KI und Beschäftigten, um die Effektivität von augmentierten Dienstleistungsinteraktionen zu steigern. Drittens müssen für die Automatisierung und/oder Augmentierung von Dienstleistungsinteraktionen sozio-technische Zusammenstellungen von KI, Dienstleistungsempfänger und -erbringer erneuert werden, um eine erfolgreiche Dienstleistungserbringung zu gewährleisten. Diese Herausforderungen adressierend wird in dieser kumulativen Dissertation Wissen für die human-zentrierte Gestaltung von KI-basierten Lösungen und deren Integration in Arbeitssysteme entwickelt, um eine hybride Erbringung von text-basierten online Dienstleistungen zu ermöglichen. Als Anpassung und Erweiterung von KA und HIS, können mit KI-basierten virtuellen Agenten und Nutzeroberflächen dadurch einerseits hybride konsekutive online Dienstleistungsinteraktionen realisiert werden, um das Scheitern von KA durch Übergaben von Anfragen an Beschäftigte zu vermeiden. Andererseits kann mit KI-basierten virtuellen Agenten und Nutzeroberflächen eine

bedarfsgerechte Unterstützung von Beschäftigten in hybriden simultanen online Dienstleistungsinteraktionen erreicht werden.

Forschungsdesign

Bei dieser Forschungsarbeit handelt es sich um eine kumulative Dissertation, die den Gesetzmäßigkeiten des Forschungsparadigmas Design Science Research (DSR) folgt, um das definierte Forschungsziel zu adressieren. Die durchgeführten Forschungsaktivitäten beziehen sich auf die neun enthaltenen Publikationen und wurden anhand von sechs Forschungsfragen strukturiert, die sich auf die drei DSR-Zyklen aufteilen. Motiviert durch die unterschiedlichen Erkenntnisinteressen im Rahmen der Beschreibung des Problemraums und Herleitung eines Lösungsraums, sind in dieser kumulativen Dissertation eine Reihe von Forschungsmethoden zur Anwendung gekommen. Mit Literaturrecherchen wurde bestehendes wissenschaftliches Wissen erfasst, um Forschungslücken zu identifizieren und deskriptives als auch präskriptives Wissen für die kumulative Erzeugung von Wissensbeiträgen zu berücksichtigen. Mit der Entwicklung einer Taxonomie wurde zu einem verbesserten Verständnis für die Integration von KI in Arbeitssysteme im Bereich text-basierter online Dienstleistungen beigetragen. Im Rahmen der Entwicklung des entstandenen Designwissens wurden unterschiedliche qualitative Methoden angewendet. Um die realweltlichen Herausforderungen als auch Kriterien für Lösungen zu identifizieren, wurden semi-strukturierte Interviews durchgeführt. Darüber hinaus wurden Interviews und Fokusgruppen verwendet, um das entstandene Designwissen und dessen Instanziierung zu evaluieren. Die erhobenen Daten wurden mittels qualitativer Inhaltsanalysen ausgewertet. Mit der Absicht den Einfluss entstandener Designentitäten in Form von Prototypen auf Individuen zu evaluieren, wurden quantitative Methoden angewendet. Die primären und sekundären Daten wurden mit unterschiedlichen statistischen Verfahren ausgewertet.

Ergebnisse

Die kumulative Dissertation präsentiert validiertes Wissen für die human-zentrierte Gestaltung von KI-basierten Lösungen und deren Integration in Arbeitssysteme für die hybride Erbringung von text-basierten online Dienstleistungen. Die Ergebnisse unterteilen sich in Beiträge mit deskriptivem (Ω) und präskriptivem (λ) Charakter. Das Ω-Wissen bezieht sich einerseits auf die Erfassung operationaler Herausforderungen in Bezug auf prozessuale Strukturen und Aufgaben in Arbeitssystemen im Bereich von online Dienstleistungen. Andererseits werden Archetypen für die Bestimmung der Konstellationen bestehend aus KI, Dienstleistungsempfänger und -erbringer erneuert. Die λ-Wissensbeiträge werden in zwei Formen präsentiert. Mit einem Modell, Designprinzipien und instanziierten Designentitäten wird Designwissen vorgestellt, das für die Integration und Erstellung von KI-basierten Lösungen verwendet werden kann. Als Bestandteil automatisierter und/oder augmentierter Dienstleistungsinteraktionen können die entstehenden virtuellen Agenten oder Nutzeroberflächen für die hybride Erbringung text-basierter online Dienstleistungen eingesetzt werden. Neben diesem detaillierten Designwissen werden Designmuster präsentiert, die das akkumulierte Designwissen mittels vier Problem-Lösungs-Paaren aggregiert.

Beitrag

Die Dissertation leistet mit dem validierten Wissen für die Integration und das Design human-zentrierter KI-basierter Lösungen für die hybride Erbringung von text-basierten online Dienstleistungen einen Beitrag zur Forschung in den Bereichen online Dienstleistungserbringung, Zukunft der Arbeit und Mensch-KI-Interaktion. Die Ergebnisse liefern einen Ansatz für den Einsatz von KI für online Dienstleistungserbringung, um bestehende Limitationen bei der Automatisierung zu überwinden und Verbesserungen in der Augmentierung zu erzielen. Das präsentierte Designwissen, in Form von Designprinzipien und Designmustern für die Erstellung KI-basierter Lösungen für hybride Dienstleistungserbringung, kann in der Forschung verwendet werden, um eine Synergie zwischen Automatisierungs- und Augmentierungsansätzen herzustellen, indem diese miteinander kombiniert werden. Dadurch können die Vorteile der Abhängigkeit zwischen den KI-Ansätzen realisiert werden. Das vorgestellte Designwissen kann daher als Vorlage zur Verwendung in verwandten Forschungsdomänen dienen. Im Zusammenhang mit Untersuchungen zu Zukunft der Arbeit wird die Eignung der Adoption einer sozio-technischen Linse durch die Ergebnisse der Dissertation bestätigt, um die durch die Integration von KI entstehenden Interdependenzen zwischen den sozialen und technischen Subsystemen in der Neugestaltung von Arbeitsprozessen und der Verteilung von Aufgaben zu berücksichtigen. Ferner hilft die Involvierung von Beschäftigten bei der Identifizierung wertestiftender Einsatzszenarien, indem bestehende operative Herausforderungen gelindert und die Kombination menschlicher und KI-basierter Fähigkeiten gezielt und menschenzentriert vorgenommen werden. Im Kontext der Erbringung von online Dienstleistungen präsentiert die Dissertation zudem Lösungen für die dyadische Delegation von Aktivitäten zwischen KI und Beschäftigten, um unterschiedliche Formen der hybriden Zusammenarbeit zu ermöglichen. Das präsentierte Designwissen liefert zudem Erkenntnisse für die Gestaltung der Mensch-KI-Interaktion in automatisierten und augmentierten Dienstleistungsinteraktionen. Eine humanzentrierte Unterstützung der Dienstleistungserbringer durch KI in augmentierten Dienstleistungsinteraktionen kann durch eine zeitlich abgestimmte, übersichtliche Präsentation von relevanten Informationen erreicht werden. Dadurch können Dienstleistungserbringer, in der durch die Synchronität der Interaktion entstehenden dynamischen Anfragebearbeitung, angemessen bei der Informationsverarbeitung, Entscheidungsfindung und Problemlösung unterstützt werden. In automatisierten Dienstleistungsinteraktionen können Dienstleistungsempfänger durch Strukturvorgaben der KI während der Interaktion unterstützt werden relevante Informationen zu liefern, die eine Fortsetzung der Bearbeitung durch Dienstleistungserbringer nach Übergaben erleichtern.

Die Ergebnisse der Dissertation haben Implikationen für die Praxis, da sie Unternehmen unterstützen können KI in Arbeitssysteme im Bereich online Dienstleistungen zu integrieren und für die hybride, text-basierte online Dienstleistungserbringung im Rahmen von Automatisierungs- und/oder Augmentierungsstrategien zu gestalten. Die festgestellte Eignung eines sozio-technischen Ansatzes für Arbeitsanalysen ermöglicht es Unternehmen unter Einbezug ihrer Beschäftigten den Einsatz von KI so zu bestimmen, dass bestehende Herausforderungen im operativen Betrieb adressiert werden. Darüber hinaus kann die Taxonomie verwendet werden, um Gestaltungsentscheidungen für die Implementierung von KI-basierten Lösungen zu strukturieren. Das präsentierte präskriptive Designwissen kann in Unternehmen verwendet werden, um KI-basierte Lösungen zu gestalten, die eine hybride Erbringung text-basierter online Dienstleistungserbringung ermöglichen. Die entstehenden Lösungen können die Robustheit gegenüber Fehlfunktionen bei automatisierten sowie die Zusammenarbeit zwischen Dienstleistungserbringern und KI bei augmentierten Dienstleistungsinteraktionen verbessern.

Limitationen

Die Ergebnisse der kumulativen Dissertation müssen vor dem Hintergrund einiger Limitationen betrachtet werden. Durch die Konzeptualisierung des Problemraums wurden realweltliche Herausforderungen und Anforderungen für Lösungen identifiziert. Durch die Selektion von Unternehmen und Anwendungsfällen ist eine Generalisierbarkeit der erfassten praxisrelevanten Herausforderung nicht zwingend gegeben. Um eine repräsentative Auswahl von Unternehmen und Beschäftigten in zwei Anwendungskontext zu gewährleisten, wurden daher etablierte Sampling-Methoden verwendet. Zudem besteht das Risiko, dass die gewonnen Erkenntnisse, die auf qualitativen Daten beruhen, durch die Interpretation der beteiligten Forschenden beeinflusst wurden. Um dieses Risiko zu minimieren, wurden etablierte Kodierungsmethoden verwendet und eine erhöhte Objektivität in der Analyse durch den Einbezug mehrerer Forschungspersonen erzielt. In der Herleitung des Lösungsraums wurde Designwissen unter Berücksichtig bestehender wissenschaftlicher Erkenntnisse generiert. Die getroffene Auswahl und Nicht-Berücksichtigung relevanter Literatur können einen Einfluss auf die erzielten Ergebnisse nehmen. Um einen Beitrag über bestehende wissenschaftliche Erkenntnisse hinaus zu erzielen, wurden etablierter Methoden für eine objektive, valide und reliable Selektion von Literatur verwendet. Weitere Limitationen beziehen sich auf die Evaluierung des entstandenen Designwissens. Durch die Instanziierung und Evaluierung des Designwissens in einer geringen Anzahl von Unternehmen in den beiden untersuchten Anwendungskontexten ist die Projizierbarkeit des Designwissens eingeschränkt. Zudem ist die Aussagekraft der Ergebnisse durch die Simulation von Dienstleistungsempfängern in semi-naturalistischen Evaluationssettings eingeschränkt. Darüber hinaus ist die Validierung der hergeleiteten Designmuster auf die Evaluierung ihrer Bestandteile in Form detaillierter Designprinzipien aus den Publikationen beschränkt.

Ausblick

Durch die Ergebnisse der kumulativen Dissertation ergeben sich Anknüpfungspunkte für zukünftige Forschung in Bezug auf die Integration und Gestaltung von KI für die Erbringung von online Dienstleistungen. Im Rahmen der Untersuchung zu der Integration von KI-basierten Lösungen in Arbeitssysteme für die Erbringung von online Dienstleistungen kann die Involvierung von Beschäftigten für die Bestimmung des Einsatzes und der Eigenschaften von KI durch Low-Code-Entwicklungsansätze ausgedehnt werden. Zudem sollte zukünftig die Perspektive von Dienstleistungsempfängern in der Bestimmung von Anforderungen an KI-basierte Lösungen und ihre Zufriedenheit mit hybrider online Dienstleistungserbringung in einem größeren Umfang berücksichtigt werden. Um Erkenntnisse über die Vor- und Nachteile der Strategien zu generieren, sollte die Effektivität von hybrider online Dienstleistungserbringung im Rahmen von Automatisierungs- und Augmentierungsansätzen oder deren Kombination durch deren Vergleich evaluiert werden. Zukünftige Untersuchungen zu der Gestaltung von KI-basierten Lösungen für die Erbringung von online Dienstleistungen sollten sich mit der Augmentierung von Dienstleistungsinteraktionen befassen in denen KI für Dienstleistungsempfänger sichtbar ist. In diesem Zusammenhang gilt es, geeignete Eigenschaften für das Verhalten und die Repräsentation von KI zu bestimmen. Weiterhin sollte Designwissen für die Entwicklung von Lösungen hergestellt werden, die weitere Formen der Übergaben zwischen KI und Dienstleistungserbringer ermöglichen. Als ein weiterer Aspekt kann die Gestaltung der Mensch-KI-Interaktion in hybriden simultanen online Dienstleistungsinteraktionen ausgedehnt werden, indem sie auf die Bedürfnisse von Beschäftigten mit unterschiedlichen Charakteristika zugeschnitten wird. Mit individuellen Konfigurationen in Nutzeroberflächen von KI können passgenaue Unterstützungsformate für Beschäftigte mit unterschiedlichen Erfahrungslevels hergestellt werden.

Table of Contents

I. List of Figures

The figures of the articles included in this dissertation thesis are not listed.

II. List of Tables

The tables of the articles included in this dissertation thesis are not listed.

III. List of Abbreviations

AI	Artificial intelligence
CA	Conversational agent
DP	Design principle
DSR	Design science research
HCI	Human-computer interaction
HIS	Hybrid intelligence system
IS	Information systems
IT	Information technology
ML	Machine learning
MR	Meta-requirement
NLP	Natural language processing
RG	Research goal
RQ	Research question
SE	Service employee
SK	Service seeker

The abbreviations in the articles included in this dissertation thesis are not listed.

1 Introduction

1.1 Motivation and Problem Statement

A volatile and complex world with competitive conditions pressures organizations and institutions to react adaptively to dynamically changing demands. To meet these environmental requirements, organizations undergo transformational processes by implementing innovative digital technologies (Yoo et al., 2012). With its potential to cost-effectively optimize operational efficiency and increase productivity at the individual, departmental, and organizational levels, artificial intelligence (AI) has sparked a high level of attention in practice and information systems (IS) research (Collins et al., 2021; Davenport & Ronanki, 2018). Fueled by advances in machine learning (ML) methods, AI can determine probabilistic outcomes based on existing data and continuously improve through learning strategies (Haenlein & Kaplan, 2019; Russell & Norvig, 2009). This allows AI to emulate human behavior by performing activities to achieve specific goals. Driven by these capabilities, increasing digitization, and mass datafication, organizations are incrementally using AI to automate or augment their business processes, tasks, and activities (Chui et al., 2018; Coombs et al., 2020; Lacity & Willcocks, 2021). As a result, the adoption and dissemination rate of AI as part of automation or augmentation strategies is steadily increasing across industries (Ghosh et al., 2019).

One sector that is undergoing a disruptive transformation owing to the introduction of AI technologies and progressive digitization is service (Bock et al., 2020; M.-H. Huang & Rust, 2018). Harnessing the advancements in information technology (IT), organizations have expanded the range of technology-mediated service interfaces to meet the increased demands of service seekers (SKs). By providing service through service employees (SEs), technology, or a combination thereof, a large proportion of intangible services are delivered online (Barrett et al., 2015; McLean & Osei-Frimpong, 2017; Patrício et al., 2008). The accessibility and simplicity of delivering knowledge- and information-intensive services related to people (e.g., consulting) or their objects (e.g., IT support) have thereby been elevated (Rust & Huang, 2014). In this context, the deployment of AI-based technologies is fundamentally affecting the efficiency and effectiveness of external (e.g., e-commerce, finance, and insurance) and internal (e.g., IT support and human resources) online service request handling (M.-H. Huang & Rust, 2018; Y. Xu et al., 2020). To fulfill SKs' demands for personalized, bidirectional, and chat-based service encounters with immediate feedback (Adam et al., 2021; Lehrer et al., 2018), AI-based solutions, represented as virtual agents along with an identity or embedded in user interfaces, are used (Glikson & Woolley, 2020). As part of the automation approach, AI-based self-service solutions represented as virtual agents enable SKs to resolve their requests themselves. This scalable and paralleled form of autonomous service encounter can increase the efficiency of online service delivery and partly substitute SEs' task of processing routine requests (Kleinschmidt et al., 2020; Larivière et al., 2017; Marinova et al., 2017). To improve the service experience of these self-service encounters, researchers have devoted effort to creating intuitive, personalized, and interactive self-service solutions using these AI-enabled virtual agents. A prominent form is conversational agents (CAs), which are represented by virtual identities (Gnewuch et al., 2017; Verhagen et al., 2014). Being able to provide information, make decisions, and execute appropriate actions in humanlike interactions, CAs can autonomously reply to SKs' requests (Diederich et al., 2022). Besides the efforts to automate online service operations, augmentation approaches have recently emerged to join forces between SEs and AI to provide online service delivery (Wilson & Daugherty, 2018). The complementary abilities of SEs (e.g., abstract thinking, creativity, and emotional capacity) and AI (e.g., analytical ability and speed) can be used to compensate for each other's limitations and create hybrid intelligence through collaboration (Dellermann, Ebel, et al., 2019; Kamar, 2016). This hybrid intelligence involves reciprocal, coevolutionary learning, enabling the continuous improvement of outcomes (Amershi et al., 2015; Dellermann, Ebel, et al., 2019). To facilitate this collaboration and learning, hybrid intelligence systems (HISs) comprise AI that is either embedded or virtually represented as an agent. In the context of online service encounters, SE and AI can augment each other as part of HISs to improve the effectiveness of interactions with SKs (e.g., satisfaction) (Henkel et al., 2020). More specifically, the combination of AI's rapid processing of textual input and its presentation of suitable information with SEs' ability to understand semantically complex requests, act on unpredictable situations, and be empathic can be beneficial for online service encounters.

Overall, AI's ability to automate or augment cognitive tasks in service can contribute to optimized productivity for text-based online service delivery (Coombs et al., 2020; M.-H. Huang & Rust, 2018). However, leveraging AI's potential of AI vis-à-vis online service is not a self-fulfilling endeavor.

First, the automation or augmentation of online service activities with AI-based solutions still comes with drawbacks and creates a trade-off between efficient and effective service delivery. The automation of service encounters with CAs can help to reliably process low-complexity requests that have a high volume and can be standardized (Davenport et al., 2020). Nevertheless, their bounded capabilities can lead to the failure to autonomously handle complex or emotional SK requests (M.-H. Huang & Rust, 2018). This inability to answer the full range of possible requests entails the risk of deconstructing value through service failure (Castillo et al., 2021). By augmenting service encounters, the diversity of requests can be addressed by combining the capabilities of AI and SEs in HISs. This approach is suited for average complexity requests, which are characterized by a high volume but require high variability in solutions (Wirtz et al., 2018). However, there is potential to increase the effectiveness of augmented service encounters, as augmentation with HISs is still in its infancy. Thus, both strategies still need to be improved by considering suitable AI solutions. In addition, insights are needed into how a combination of the approaches can be achieved to avoid the trade-off between efficient and effective online service encounters (Benbya et al., 2021; Raisch & Krakowski, 2021).

Second, online service delivery represents a socio-technical work system that requires the orchestration of the needs, capabilities, and activities of SKs, SEs, and AI to produce quality outcomes (Alter, 2020; Bock et al., 2020). Regardless of whether one or both of the AI strategies is applied, the social and technical components of a work system need to be connected to ensure the success of online service production. In automation approaches, activities for online service delivery should be distributed between AI and SE to prevent impending service failures in automated service encounters. In addition, in augmentation approaches, optimal results can be achieved by purposefully integrating the capabilities of AI and SEs in augmented service encounters (Vassilakopoulou et al., 2022). To establish this hybrid form of online service delivery, the goals, roles, processes, and activities of SEs and AI need to be aligned and interconnected. However, research on the interrelationships between SE, SK, and AI, as well as their embeddedness in work and process structures within the socio-technical system of online service delivery, is lacking (Bock et al., 2020; Keyser et al., 2019). Hence, considering the two approaches, research is needed to determine the integration of AI into work systems and to define the configurations and forms of interaction between AI, SE, and SK for online service encounters.

To overcome the current drawbacks and leverage the untapped potential of automation or augmentation strategies for text-based online service, there is a need for AI-based solutions that can be integrated into online service delivery work systems to enable a hybrid form of service production. In the context of automation approaches, previous research has addressed the limitations of CAs in regard to the autonomous handling of SK requests using automated service recovery strategies to avoid conversational breakdowns (Benner et al., 2021; Kvale et al., 2020). As these strategies can repeatedly fail to prevent conversational breakdown, there is a need for hybrid scenarios in which SEs avert the complete service failure of automated service encounters. For these fallbacks, handovers can be implemented whereby SK requests are relayed from CAs to SEs for further processing (Ashktorab et al., 2019; Schuetzler et al., 2021). This hybrid service recovery strategy requires the redesign of service processes to integrate the existing work practices of CAs and SEs by considering the socio-technical dependencies in online service delivery work systems. In addition, in regard to continuing request processing after handover, SEs should be supported by making information from the CA-SK interaction available to them. To achieve this, CAs need to be adapted for interaction with SKs, and a user interface needs to be developed so that information can be collected, transferred, and presented to SEs. However, the human-centered design knowledge necessary for realizing handovers that meet the requirements of SKs and SEs has been missing (Poser et al., 2021). In the context of augmentation approaches, the investigation of hybrid service delivery by means of HISs has been initiated to create optimal conditions for collaboration between AI and SE. In the field of online service delivery, there has been initial research on the augmentation of decision-making (Graef et al., 2020) and emotion regulation (Henkel et al., 2020). To fully leverage the advantages of HISs for joint task execution and mutual learning, human-computer interaction (HCI) has to be designed. More specifically, suitable input and output formats of AI, that can be represented as a virtual agent or embedded in a user interface, must be determined. However, human-centered design knowledge for HISs that is adapted to the situational circumstances of online text-based service delivery and human needs remains still scarce.

In sum, this dissertation addresses these research gaps and AI's potential for text-based online service delivery. By adapting and complementing existing CA and HIS solutions, knowledge is developed to create AI-based solutions that are represented as a virtual agent or embedded in a user interface to allow hybrid online service encounters. In doing so, integration points for service processes and tasks are determined, and knowledge for their design is generated.

1.2 Research Goal and Research Questions

The current research lacks knowledge of the integration and design of AI-based solutions to enable hybrid, text-based online service delivery. Facilitating the creation of solutions that are represented as virtual agents or embedded in user interfaces, this design knowledge could improve robustness to failure in automated encounters, as well as collaboration between SEs and AI, in augmented service encounters. Consequently, the presented motivation and problem statement result in the following overall research goal (RG) for this dissertation:

RG	**Enable hybrid text-based service delivery by developing validated design knowledge for AI and its integration as embedded or virtual agent solutions into online service delivery work systems.**

Guided by the motivation to produce design knowledge, the design science research (DSR) paradigm is adopted in this dissertation. To systematize research activities in pursuit of the RG, the research questions (RQs) are developed according to the three established DSR cycles of relevance, rigor, and design (Hevner, 2007; Thuan et al., 2019). The consideration of real-world challenges and suitable scientific knowledge for the development of design knowledge is thereby ensured (Hevner & Chatterjee, 2010). Overall, six RQs are addressed using a cumulative approach (see Figure 1).

To begin, the status quo in online service delivery work systems is analyzed to identify existing challenges and requirements in the environment for solutions to be generated. As insights into the interplay between social and technical systems are scarce, current problems in online service delivery work systems are analyzed from a socio-technical perspective. In addition, practice-oriented requirements for generating human-centered design knowledge for the implementation of hybrid text-based online service delivery are collected. Accordingly, the first RQ is defined as follows:

RQ 1a	**What are the challenges in online service work systems, and which requirements need to be considered for establishing hybrid text-based online service delivery?**

To tackle the identified challenges, existing scientific knowledge should be considered to inform the derivation of suitable solutions that allow hybrid text-based online service delivery. By systematically analyzing knowledge for the design and integration of AI-based solutions, existing approaches that help to compensate for prevailing limitations and leverage improvement potential in automating and augmenting online service encounters can be considered. Thereby, knowledge gaps can be identified and research activities can be determined to address them. Therefore, the RQ is as follows:

RQ 1b	**What is the current state of research regarding the design and utilization of AI-based solutions for hybrid text-based online service delivery?**

The first two questions motivate and determine the entry point for this research project. The subsequent research activities, which are directly related to the RG, aim to enable hybrid text-based online service delivery by developing design knowledge for the construction of AI-based solutions and their integration into online service delivery work systems. For the automation and/or augmentation of service production in online service encounters to succeed, AI-based solutions must be integrated into the socio-technical system of online service delivery work systems. However, there has been a lack of knowledge on the integration of AI-based solutions and the design of socio-technical interrelationships between SE, SK, and AI for hybrid text-based online service delivery. This leads to the first part of the second RQ:

RQ 2a	**How can AI-based solutions be integrated into online service delivery processes allowing a hybrid and text-based service production?**

For the identified integration points and role definitions of SEs, SKs, and AI, design knowledge and solutions represented as embedded AI or AI-enabled virtual agents are needed to enable hybrid online service delivery. As part of the automation approaches, there is a need for human-centric design knowledge and solutions that enable hybrid consecutive online service encounters to avoid service failure. Therefore, CAs that are represented as virtual agents need to be designed in such a way that they can avert impending conversational breakdowns by handing requests over to SEs. As an extension, a user interface is needed to enable SEs to continue processing SK requests after handover. In the context of augmentation approaches, HISs comprising AI that is represented as a virtual agent or embedded in a user interface need to facilitate the formation of a symbiosis between SEs and AI. However, there has been a lack of human-centric design knowledge to adapt this form of hybrid, simultaneous online service encounter to the conditions of text-based online service encounters. Consequently, the second part of the second RQ is as follows:

RQ 2b	**How can human-centered AI as embedded or virtual agent solutions for hybrid text-based online service encounters be designed?**

The output of the previous RQs has to be evaluated, validated in, and transferred into practice. Accordingly, the utility, usefulness, and effectiveness of the design knowledge and its instantiations in the environment should be assessed. To verify and transfer the created artifacts, the following RQ is posed:

RQ 3a	**How does AI and its integration as embedded or virtual agent solutions for hybrid text-based online service encounters affect service production in online service work systems?**

Based on the results obtained through the preceding research activities, contributions to the knowledge base should emerge. Accordingly, the last RQ is as follows:

RQ 3b	**Which contributions can be added to the knowledge base about the design of AI and its integration as embedded or virtual agent solutions into online service delivery work systems to enable hybrid online service encounters?**

These six RQs guide the systematic examination of the overarching RG in a cumulative process. The required research activities were completed with nine individual articles that are part of this thesis. Each of these articles contributes to answering one or multiple RQs. The relationship between the articles and concrete research activities and how they are linked to respective RQs is outlined in Section 3.2.

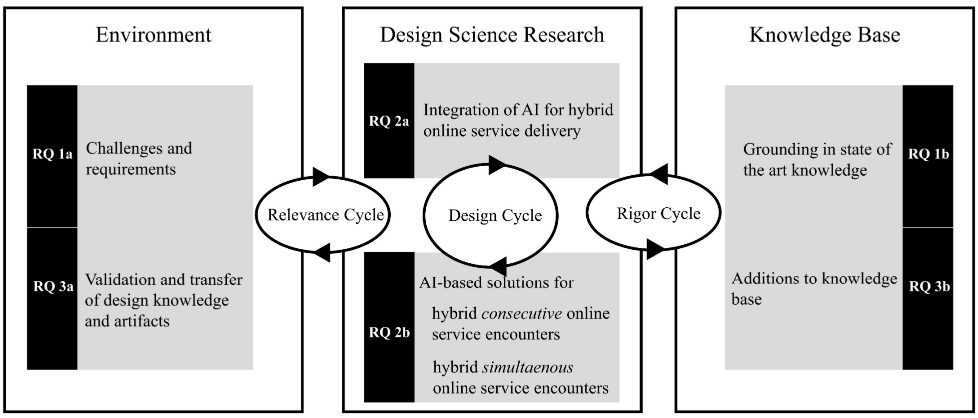

Figure 1. Assignment of RQs to DSR cycles (Hevner, 2007), adapted

1.3 Outline of the Thesis

This thesis is composed of a wrapper and nine publications. The structure of these components is illustrated in Table 1.

The wrapper commences with introductory content by delineating the motivation, problem statement, and RQs of the thesis. In Section 2, the theoretical and conceptual foundations are presented. The research design, introduced in Section 3, describes the applied research paradigm, strategy, and methods. Thereafter, the articles that are related to and included in the dissertation are presented in Section 4. In Sections 5 and 6, the theoretical and practical contributions of the thesis are presented and discussed. The limitations of this thesis are reflected in Section 7. The implications for further research are provided in Section 8. Finally, Sections 9 to 17 comprise the articles of this cumulative dissertation.

Table 1. Thesis outline

<table>
<tr><td rowspan="2">Wrapper</td><td>1. Introduction</td><td>2. Theoretical Foundations</td><td>3. Research Design</td><td>4. Publications</td></tr>
<tr><td>5. Theoretical Contributions</td><td>6. Practical Contributions</td><td>7. Limitations</td><td>8. Implications for Further Research</td></tr>
<tr><td rowspan="9">Publications</td><td>9. Article 1</td><td colspan="3">(Re)Designing IT Support: How Embedded and Conversational AI Can Augment Technical Support Work</td></tr>
<tr><td>10. Article 2</td><td colspan="3">Integration of AI into Customer Service: A Taxonomy to Inform Design Decisions</td></tr>
<tr><td>11. Article 3</td><td colspan="3">Hybrid Teamwork: Consideration of Teamwork Concepts to Reach Naturalistic Interaction between Humans and Conversational Agents</td></tr>
<tr><td>12. Article 4</td><td colspan="3">Design and Evaluation of a Conversational Agent for Facilitating Idea Generation in Organizational Innovation Processes</td></tr>
<tr><td>13. Article 5</td><td colspan="3">May the Guide Be with You: CA-facilitated Information Elicitation to Prevent Service Failure</td></tr>
<tr><td>14. Article 6</td><td colspan="3">Hybrid Service Recovery: Design for Seamless Inquiry Handovers between Conversational Agents and Human Service Agents</td></tr>
<tr><td>15. Article 7</td><td colspan="3">Don’t Throw It Over the Fence! Toward Effective Handover from Conversational Agents to Service Employees</td></tr>
<tr><td>16. Article 8</td><td colspan="3">Let’s Team Up with AI! Toward a Hybrid Intelligence System for Online Customer Service</td></tr>
<tr><td>17. Article 9</td><td colspan="3">Design and Evaluation of an Employee-facing Conversational Agent in Online Customer Service</td></tr>
</table>

2 Theoretical Foundations

By describing, delineating, and defining the core theoretical and conceptual foundations, this section provides the current state of the research and identifies existing knowledge gaps that are addressed in this thesis. First, the role of AI in socio-technical systems is presented. Second, online service delivery and the interplay of SKs, SEs, and IT in these working systems are described. Third, the application of AI-based solutions and the role of human-AI interaction in the automation and augmentation of online service encounters are addressed.

2.1 AI in Socio-technical Systems

Research on AI has a long tradition and is pursued across several disciplines, such as mathematics, neuroscience, and computer science (Russell & Norvig, 2009). In IS research, studies typically examine the capabilities of AI in organizational environments by mimicking human behavior and thinking, inter alia, to make decisions or solve problems (Benbya et al., 2021; Krogh, 2018). In this context, a common definition of AI is “the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem-solving, decision-making, and even demonstrating creativity” (Collins et al., 2021; Rai et al., 2019, p. iii). These characteristics classify AI as narrow (or weak) with contextual, restricted intelligence, as general AI with human-level capabilities does not yet exist (Benbya et al., 2021; Haenlein & Kaplan, 2019; Raj & Seamans, 2019). According to Russell and Norvig (2009), the investigation of AI in IS research is guided by four approaches: (1) the Turing test approach, (2) the cognitive modeling approach, (3) the laws of thought approach, and (4) the rational agent approach. The aim of the first two approaches is to create AI solutions that are able to perform tasks at a human level, and the aim of the second is to apply human processes to handle input and produce the same outcome as humans. Regarding the laws of thought approach, AI is built to follow rational rules and apply logic to generate output. Finally, the rational agent approach focuses on agentic AI solutions that are capable of perceiving their environment, responding to or proactively inducing change, and interacting with humans to complete their activities or assist others in doing so (Baird & Maruping, 2021; Jennings et al., 1998; Russell & Norvig, 2009). Thus, AI is supposed to achieve the “best outcome or, when there is uncertainty, the best expected outcome” (Russell & Norvig, 2009, p. 4).

As AI’s humanlike capabilities can contribute to organizational transformations at several levels, different research streams intersect in the study of AI regarding, inter alia, the purpose of the application, its affordances, and its effects (e.g., Brynjolfsson & McAfee, 2014; Krakowski et al., 2022; Makarius et al., 2020; Raisch & Krakowski, 2021). One stream of IS research has focused on the automation capabilities of AI by exploring its application to process automation, generation of cognitive insights, and enablement of cognitive engagements (Collins et al., 2021). In the former, administrative processes are made efficient through the autonomous manipulation of information across different systems (Davenport et al., 2020). In the other two use cases, ML and natural language processing (NLP) are employed to analyze and interpret data or interact with users via natural language and present suitable output (Benbya et al., 2021; Davenport & Ronanki, 2018). These AI applications can help organizations perform routine administrative, transactional, analytical, and problem-solving tasks autonomously (Coombs et al., 2020; M.-H. Huang & Rust, 2018; Murray et al., 2021). This, in turn, leads to efficient organizational operations and generates potential for value creation. Another stream of research covers the application of AI to augment tasks. This involves the combination of human and AI capabilities to enable collaborative work and mutual learning (Dellermann, Calma, et al., 2019). To leverage the potential for elevated effectiveness in task work, previous publications have explored the improvement of, inter alia, decision-making behavior, problem-solving, and creativity in several application domains (Jarrahi, 2018; Krogh, 2018; Shrestha et al., 2019). Related to affordances and effects, prior research has also addressed the underlying purpose of AI application. In this context, a contradiction between the automation and augmentation approaches has been observed (Brynjolfsson & McAfee, 2014). Therefore, companies apply only one approach at one point in time for a specific task. This provokes a trade-off between efficiently and effectively accomplishing tasks (Raisch & Krakowski, 2021). In addition, previous work has revealed that focusing on one strategy has detrimental effects on companies, for example, as the progressive expansion of automatable activities over time remains unexploited owing to the unused coevolutionary learning properties of augmentation (Benbya et al., 2021; Krakowski et al., 2022; Raisch & Krakowski, 2021).

Besides determining the purpose of the application, research has addressed the impact using AI to automate and augment work tasks in organizations (Østerlund et al., 2021). These investigations are increasingly guided by socio-technical perspectives that extend a purely technical system view of AI. This involves describing and analyzing organizations in terms of the interrelationships between humans, technology, and outcomes (Bostrom & Heinen, 1977; Morgan-Thomas et al., 2020). Different roles for AI and humans have been investigated to explore the future of work scenarios in socio-technical systems. These roles predominantly appear in three forms: (1) AI performs activities without human involvement; (2) AI and humans work alongside each other, and each contributes to task processing; and (3) both operate as a unit to achieve task goals through direct collaboration (Grønsund & Aanestad, 2020; Rai et al., 2019; vom Brocke et al., 2018). While the first configuration is used for automation, the other two forms are applied for the augmentation of tasks. Addressing these different roles of AI, scholars have investigated how AI affects the organization of work, considering the definition of tasks and their coordination and allocation (Faraj et al., 2018; Makarius et al., 2020). Moreover, in previous work, tasks haven been classified according to their characteristics (e.g., availability of solutions and analyzability) and defined activities that can be performed by either AI and humans alone or in collaboration (Alter, 2020, 2022; Brynjolfsson & McAfee, 2014; Crowston & Bolici, 2020). In addition to the abovementioned aspects, past publications have dealt with additional socio-technical topics, for example, addressing the creation of a process for introducing AI into organizations from an employee perspective (Makarius et al., 2020), the design of engagement with AI (Morgan-Thomas et al., 2020), and the formation of principles that govern the delegation of tasks between AI and humans (Baird & Maruping, 2021). In this context, research has mainly considered two different forms of AI appearances. On the one hand, virtual agents have been used to provide AI-based solutions with an identity and to represent them digitally. On the other hand, AI-based solutions that are embedded in the user interface of various applications and are not represented visually have been investigated (Glikson & Woolley, 2020).

Overall, prior research has progressively focused on using AI in organizations to augment and automate tasks by acknowledging human-technology interdependencies. However, little research has been conducted on how the interactions among humans, technology, information, and processes can be considered in determining the application of AI (vom Brocke et al., 2018). In addition, scholars call for employee participation in determining the purpose of the application of AI, the characteristics of AI solutions, and their integration into work practices (Lu et al., 2020; Østerlund et al., 2021; Wolf & Blomberg, 2019). Furthermore, insights are needed to further unlock the potential of AI by establishing synergy between the automation and augmentation of tasks for a socio-technical system by combining them (Benbya et al., 2021; Raisch & Krakowski, 2021). In this dissertation, these research gaps are addressed to determine how to ensure the purposeful integration of AI-based solutions for hybrid text-based online service delivery. To consider the core elements of online service delivery work systems in regard to their form and function, Alter’s (2013) work system concept is adopted (see Figure 2). According to work system theory, these systems are defined as the interplay between humans and/or machines that perform processes and activities using information and other resources to produce outcomes (products or services) for internal or external SKs (Alter, 2013).

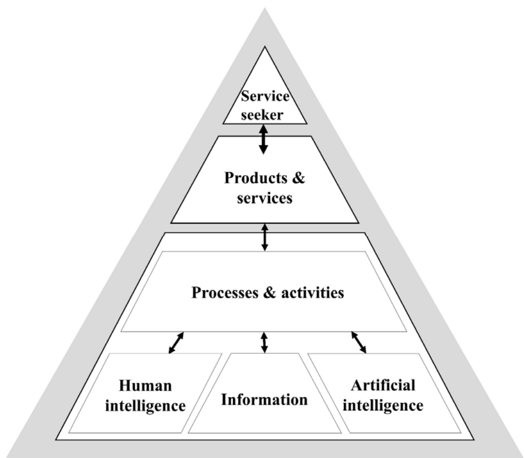

Figure 2. Work system perspective (Alter, 2013), adapted

2.2 Online Service Delivery

Service is defined as the "application of competences (knowledge and skills) by one entity for the benefit of another" (Vargo et al., 2008, p. 145). The provision of services takes place in all economic contexts and is directed at the members of one's own organization or entities (i.e., individuals or companies) outside the organizational boundaries (Alter, 2013; Rust & Huang, 2014; Vargo & Lusch, 2004). To classify different service forms, the literature distinguishes between the tangibility and the target of service. Accordingly, service delivery can be directed at people or objects (target). The corresponding service actions (tangibility) that are performed to affect the targets can or cannot be physically observed (Lovelock, 1983). Along with companies' increased service infusion and servitization, research has shifted focus from a goods-based to a service-dominant logic to investigate the importance of service, its increase in offerings, and business model transformations (Kowalkowski et al., 2017). These endeavors have been guided by the service system concept, which distinguishes between different resources (people, technology, and information) (Spohrer et al., 2007). Considering the configuration of these socio-technical resources, service design research has focused on different aspects of and conditions for service value co-creation (Grenha Teixeira et al., 2017).

IS research has concentrated on the continually increasing dissemination of services delivered by or using IT. A significant proportion of this research relates to knowledge-intensive intangible services that address the needs of individuals or the state of objects. As this form of service is based on knowledge and information and is common across industries such as insurance, finance, retail, and health care, the application of IT is explored to study the combination of relevant resources to facilitate service delivery (Barrett et al., 2015; Lusch & Vargo, 2014). In doing so, the service system perspective has been adopted to consider intertwined service processes, which usually connect two complementary service environments (Golder et al., 2012; Sampson & Froehle, 2006). On the one hand, this refers to the frontstage, in which value is co-created with SKs in service encounters. On the other hand, the backstage is considered, which supports service delivery through processes and tasks that are not visible to SKs (Bock et al., 2020; Glushko & Tabas, 2008). Thereby, inter alia, the generation of competitive advantages has been investigated by focusing on transformational effects through different deployment scenarios for IT. These endeavors have shown that IT can take on one or more roles by mediating, supporting, or performing the delivery of services across different channels (Froehle, 2006; Glushko, 2010; Rust & Huang, 2014). The mediation of contact with SKs via IT has been studied to enable online service offerings (e.g., chat and email) and to overcome the co-locatedness of SEs and SKs in regard to the delivery of intangible services (Froehle & Roth, 2004; Keyser et al., 2019). In addition, IS research has been investigated to support the documentation and retrieval of knowledge related to the target (e.g., data on SKs) or the execution of required service actions (e.g., the solution knowledge base) to address the knowledge intensity of intangible service delivery (Kankanhalli et al., 2011; Libai et al., 2020). Furthermore, self-service technologies have been addressed to allow SKs to produce services themselves by interacting with applications without the involvement of SEs (Bitner et al., 2000; Meuter et al., 2000). Overall, scientific findings show that operational performance improves with the use of IT (Brady et al., 2002).

In response to these opportunities for improvement, an extensive stream of research focusing on the application of IT in the frontstage has emerged. More specifically, online service encounters, in which SKs interact with a service represented by SEs or technology have been studied (Froehle, 2006; Larivière et al., 2017; Meuter et al., 2005). With respect to these interactions that involve the application of IT, the literature distinguishes between forms that require different levels of interactivity between the service provider and recipients (Bolton & Saxena-Iyer, 2009; Wünderlich et al., 2013). Encounters in which SKs are assumed to be highly interactive in co-creating service with SEs or self-service technology have received research attention. As the characteristics of this interactivity determine the service quality, experience, and satisfaction of SKs, the expectations and requirements of internal and external SKs have been investigated (Bitner & Wang, 2014; Gremler et al., 1994). The findings show that in addition to aspects of convenience that are enabled by the high availability and accessibility of service offerings, the service experience is gaining importance for SKs (Verhagen et al., 2014; Zomerdijk & Voss, 2010). The relevance of personalized interactions with a sense of social presence and interactivity with direct feedback during the encounter has thereby increased (Cheong et al., 2008; Scherer et al., 2015; van Doorn et al., 2017). IT-based self-service solutions have been shown to meet SKs' desires for high accessibility and availability of service offerings (Bitner et al., 2000; Meuter et al., 2000). However, the range of possible offerings is restricted to the delivery of transactional and information-related services. Moreover, service delivery lacks flexibility and human likeness and can fail (Meuter et al., 2000). In particular, service failure caused by self-service technology that prevents the delivery of desired outcomes can have detrimental effects on SKs' satisfaction and trust (Bitner et al., 2000; Smith et al., 1999). In contrast, IT-mediated online service delivered by SEs can facilitate responsiveness and individualization. In addition, the mediation of social presence can address SKs' need for trust and their willingness to co-create services (Wünderlich et al., 2013). Nevertheless, compared to self-service, the involvement of SEs in online service delivery can reduce its availability and efficiency (Scherer et al., 2015).

The transformation of existing services and the increase in online service offerings has gained importance owing to the growing prevalence of intangible services. However, owing to the technological dominance of online service delivery, effective approaches for the design of service encounters are still needed (Grenha Teixeira et al., 2017; Larivière et al., 2017; Manser Payne et al., 2021). Addressing this, the optimal mix of technical and human service delivery should be determined while considering SKs' demands. In this dissertation, online service delivery is defined as a work system, as online service encounters require the orchestration of processes, individuals, and technology (Alter, 2013; Spohrer et al., 2007). Representing prevalent work systems with similar characteristics across industries, this thesis focuses on customer service and internal IT support. Customer service predominantly concerns interactions with external SKs to, inter alia, help them make decisions (e.g., purchasing advice), inform them about processes (e.g., delivery information), or assist them with problems (e.g., product complaints). Internal IT support pertains to services for internal SKs, including the provision of answers to questions (e.g., the use of applications), support for projects (e.g., the installation of software), or resolution of problems (e.g., a password reset). Therefore, both work systems can be characterized by the time-critical and knowledge-dependent nature of intangible services (Froehle & Roth, 2004; Gray & Durcikova, 2005). Furthermore, in both service contexts, the service quality and its consequences are determined by the service provider's capacity to provide suitable information, solve problems, and articulate advice while consulting or maintaining products (Cheung et al., 2003; Das, 2003; Shaw et al., 2002). Based on these work systems, knowledge gaps related to hybrid service encounters in terms of their constellation of technology and humans are addressed.

2.3 AI-infused Online Service Encounters

With the growing capabilities of AI, research on online service encounters and the production of intangible services in various service contexts has been profoundly transformed, as underlying technologies with ML and NLP enable humanlike task processing (M.-H. Huang & Rust, 2021; Marinova et al., 2017). With its "flexible adaptation enabled by sensing, learning, decision-making and actions," service AI differs from general IT and can generate additional value (Bock et al., 2020, p. 317). Therefore, in the extant literature, the application of AI before, during, or after online service delivery has been addressed. Before and after contact with SKs, the benefits of AI's capability to process and analyze data have been studied. The findings have shown that AI surpasses human computational skills in producing relevant insights and actionable information (Ameen et al., 2021; Amorim et al., 2019; Davenport et al., 2020; Libai et al., 2020). In addition, AI can be used to acquire large and diverse datasets in numeric and text-based forms. Leveraging these capabilities, for instance, characteristics of SKs (e.g., past behavior, known needs, and attitudes) can be identified and segmented to customize and predict service delivery (Campbell et al., 2020; Libai et al., 2020).

The application of agentic AI during service delivery has also initiated a vast band of research. These endeavors have involved revisiting research on the role of IT in service encounters to leverage AI's capabilities with regard to NLP, data analytics, and pattern recognition (Dellermann, Ebel, et al., 2019; M.-H. Huang & Rust, 2018). In this context, different deployment scenarios have been determined, online service encounters have been reconceptualized, and the redistribution of activities between AI and SEs for service production has been examined. These investigations are motivated by the capacity of AI to perform the four relevant activities of (1) information acquisition and (2) analysis, (3) decision selection, and (4) action implementation in knowledge-intensive service encounters in a similar way to humans (Crowston & Bolici, 2019; R. Parasuraman et al., 2000). These processing capabilities allow AI to acquire information in the environment, analyze and match it with existing knowledge, make or suggest decisions based on conclusions, and recommend or execute actions that align with these decisions (Kühl et al., 2022; R. Parasuraman et al., 2000). Based on these capabilities, different constellations of the triad consisting of AI, SE, and SK have been identified and investigated. Therefore, in keeping with A. Parasurman and Grewal's (2000) service pyramid, the so-called infusion archetypes that address different roles of AI according to the underlying approaches of automation and augmentation have been determined (Keyser et al., 2019; Robinson et al., 2020) (see Figure 3). On the one hand, AI can automate the interaction with SKs and thereby fully substitute for SEs' activities (see Figure 3, I). On the other hand, AI can augment interactions. By supporting SEs invisibly to SKs, AI can assist in decision-making, problem-solving, or the individualization of the encounter (see Figure 3, II). Being visible for SKs, AI can also interact with SEs and, for instance, provide relevant information for SKs (see Figure 3, III) (Keyser et al., 2019; Ostrom et al., 2019). In the studies of these infusion archetypes, the role of AI is increasingly determined by matching its capabilities with the requirements of service encounters (M.-H. Huang & Rust, 2021; Paluch & Wirtz, 2020; Wirtz et al., 2018). In this way, scholars have determined that service requests with a utilitarian character and functional or instrumental utility (e.g., the provision of information) are suitable for autonomous processing by AI (M.-H. Huang & Rust, 2021; Robinson et al., 2020). The literature shows that AI can reliably process these types of recurring, predictable requests with low emotional and low to high cognitive complexity (Y. Xu et al., 2020). For service requests that have a relational focus, require high emotionality and analytic capabilities, AI is applied to augment service encounters. In these settings, SEs' empathic and intuitive experiential capabilities can be combined with AI's strong analytical capabilities (M.-H. Huang & Rust, 2018).

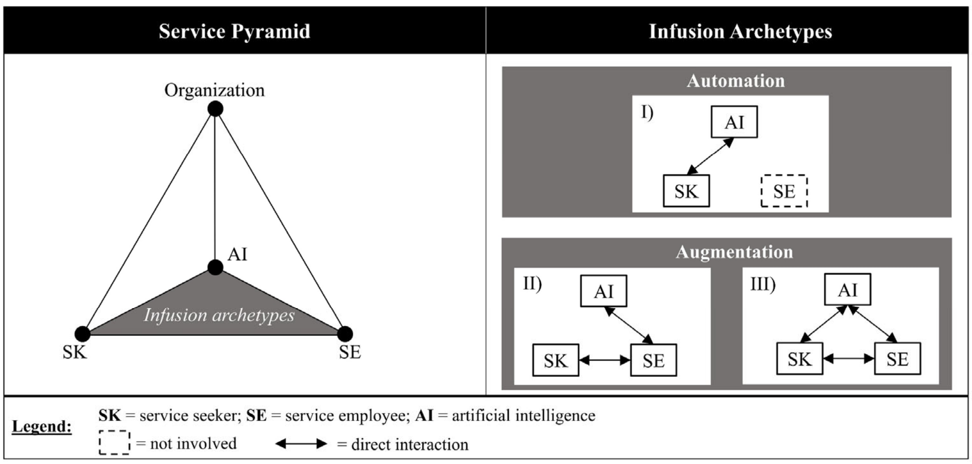

Figure 3. Infusion of AI into online service encounters (Keyser et al, 2019; Ostrom et al., 2019; A. Parasuraman & Grewal, 2000), adapted

Exploring the use of AI for these different tasks in varied roles, a large proportion of studies have focused on text-based online service delivery. Thereby, SKs' preference for live chat over other online channels (e.g., email and information portal) has been addressed (Adam et al., 2021; McLean & Osei-Frimpong, 2017). In doing so, previous research has investigated the automation and augmentation of online service encounters with CAs and HISs that are represented as AI-enabled agents or embedded AI.

2.3.1 Automated Service Encounter

To meet SKs' demands for synchronous, text- and dialog-based interaction and to increase the efficiency of online service delivery, CAs have been investigated as an AI solution for online self-service delivery that is represented as a virtual agent.

CAs are defined as software systems that interact with users via natural language in a dialog-based fashion (Bittner et al., 2019; Diederich et al., 2022). Inspired by the idea of emulating human conversations, CAs can interact with users via text or speech and are represented as agents with virtual identities (Laumer et al., 2019; McTear et al., 2016). According to their mode of interaction (speech vs. text), different terms, such as chatbot, cognitive assistant, virtual assistant, or personal assistant have been used to refer to CAs (Gnewuch et al., 2017; Hill et al., 2015). The evolution of their capabilities owing to technological developments in ML and NLP, has led to widespread investigation in various research disciplines and application contexts (Diederich et al., 2022; Knijnenburg & Willemsen, 2016; Meyer von Wolff et al., 2019). In general, two major research streams can be distinguished (Janssen et al., 2020). On the one hand, there has been an increase in the number of studies dealing with general CAs that present suitable output in response to any user request. On the other hand, there is an extensive body of knowledge on domain-specific CAs that have a limited knowledge base and are applied in narrow contexts (e.g., insurance, finance, education, and customer service). In IS research addressing the stream of domain-specific CAs, previous studies have focused on several themes or their combination. First, factors related to the management of CAs in institutions have increasingly been studied to gain insights into the implementation and continuous improvement of CAs (Janssen et al., 2020; Lewandowski et al., 2023). Second, technical features have been addressed to improve performance (e.g., NLP, learning procedures, and data management) (Edirisooriya et al., 2019; Hu et al., 2018; Io & Lee, 2017). Third, social characteristics have been investigated to achieve a humanlike user experience (e.g., Feine et al., 2019; Sands et al., 2021; Schuetzler et al., 2020; Sheehan et al., 2020).

Owing to their abilities to understand natural language input, retrieve information, execute actions in systems, and conduct engaging interactions, CAs can substitute for human activities in various application domains (M.-H. Huang & Rust, 2018; Keyser et al., 2019; Zierau, Elshan, et al., 2020). As these activities are relevant to service, CAs are commonly studied in service-related work contexts (Følstad & Skjuve, 2019; M.-H. Huang & Rust, 2021; Wirtz et al., 2018). In these endeavors, the application of CAs is examined in terms of service efficiency and experience. For instance, prior studies have shown that CAs can reliably answer frequently asked questions by mapping users' input with associated solutions based on text analytics (Dasgupta et al., 2014; Dwivedi et al., 2021; Gupta et al., 2009; Silva et al., 2018). In addition, they are increasingly able to answer more difficult questions or solve problems, such as resetting passwords, upon request (Fiore et al., 2019; Subramaniam et al., 2018; Vinyals & Le, 2015). Equipped with these capabilities, CAs can have a positive effect on SKs. By providing personalized, pleasant, and intuitive interaction, they can elevate SKs' self-service experience (Følstad & Skjuve, 2019; Svenningsson & Faraon, 2019; Verhagen et al., 2014). Additionally, CAs reduce the resolution time of SK requests, as they are constantly available and reply instantly (Y. Xu et al., 2020). Finally, the deployment of CAs affects SEs' work. Their answers reduce the volume of repetitive requests that have previously been handled by SEs (Lu et al., 2020; Waizenegger et al., 2020).

Nevertheless, CAs still have limitations in answering requests. As a result, incorrect responses (false positives) and failure to respond (false negatives) produce tedious interactions that regularly fall short of users' high expectations of CAs (Kocielnik et al., 2019; Luger & Sellen, 2016). These problems are related to deficiencies in natural language understanding and dialog management components, which interpret input incorrectly, hinder the dialog process (intent and/or entity detection), and prevent information retrieval or action execution (Kucherbaev et al., 2018). Therefore, complex and emotionally demanding requests can lead to conversational breakdowns and cause service failures. To avoid these breakdowns, previous research has addressed CA-initiated strategies using different approaches. These strategies include the automatic detection and classification of breakdowns and the execution of appropriate actions to prevent them (Reinkemeier & Gnewuch, 2022). For instance, messages are employed to prepare users for failure, users are prompted to paraphrase their input, or they are provided with options to select from to continue the dialog (Benner et al., 2021; Følstad & Taylor, 2020; Weiler et al., 2022). As these approaches can also fail, recovery strategies are needed for CAs to avert complete service failure (Jylkäs et al., 2018; Schuetzler et al., 2021). The severe effects of self-service failure on SKs' service satisfaction can thereby be prevented (Chen et al., 2021). However, the investigation of this topic is still in its infancy (Bock et al., 2020). At present, a distinction is made between recovery strategies with explanatory information and instant assistance from the service provider (Ho et al., 2020; Mozafari et al., 2021). Analyses have shown that SEs' instant involvement to rectify the failure has the most positive effects on SKs (Collier et al., 2017; Ho et al., 2020). Therefore, in the literature, fallback solutions are proposed whereby requests initially processed by CAs are handed over to SEs for further processing (Ashktorab et al., 2019; Benner et al., 2021). However, there is a research gap regarding how to implement and integrate this hybrid form of online service encounters involving SEs to recover CAs' live chat interactions with SKs (Poser, Hackbarth, & Bittner, 2022; Poser et al., 2021; Schuetzler et al., 2021). In particular, there is a need for solutions that satisfy SKs' desire for support with short waiting times and that enable SEs to recover the service interaction quickly (McLean & Wilson, 2016; Y. Xu et al., 2020).

2.3.2 Augmented Service Encounter

To augment text-based online service encounters, HISs comprising AI that is represented as a virtual agent or embedded in a user interface are increasingly used to invisibly support SEs' activities to SKs during service delivery.

HISs are defined as systems that have "the ability to accomplish complex goals by combining human and artificial intelligence to collectively achieve superior results than each of them could have done in separation and continuously improve by learning from each other" (Dellermann, Calma, et al., 2019, p. 276). In contrast to other AI-based systems, HISs enable the mutual coevolution of humans and AI during joint task processing (Dellermann, Ebel, et al., 2019). These systems thereby follow the tradition of Licklider (1960), who stated that the purpose of using AI was to complement human capabilities instead of outperforming and substituting them. Accordingly, this human-AI teaming enables compensation of the weaknesses of one entity with the strengths of the other (Akata et al., 2020; Dubey et al., 2020; Kamar, 2016). More specifically, human intelligence enables the flexible, creative, and experience-based handling of novel situations. In addition, humans can use their empathy to sense and affect the emotions of others. These strengths can compensate for AI's corresponding weaknesses. In contrast, AI's high computational capacity enables the rapid analysis of large amounts of data and the consistent generation of probability-based output. The limited cognitive human capacity can thereby be counterbalanced (Dellermann, Ebel, et al., 2019; M.-H. Huang & Rust, 2018; Wirtz et al., 2018).

Research on HISs is still relatively new and previous work has been distributed across different application domains. Independent of the application context, Dellermann, Ebel et al. (2019) determined the basic properties of HISs. Distributed across different dimensions, the resulting taxonomy gives guidance on design factors to consider (e.g., properties of the task, human-AI interaction, and AI-human interaction). Similarly, Dubey et al. (2020) present factors that are relevant for collaboration between humans and AI and that are embedded in a user interface. In addition, initial research on HISs with embedded AI in the context of online service delivery has emerged. Regarding on the comparison of ML methods, it has been shown that supporting SEs (i.e., contact types and reply templates) in handling requests for asynchronous, delayed contact with SKs increases their efficiency and reduces resolution time (Molino et al., 2018). Furthermore, the increased effectiveness of synchronous online service interaction was investigated using a case-based reasoning approach (Graef et al., 2020). In this approach, SEs were shown similar requests with solutions from the past matching requests from SKs. Apart from HISs with embedded AI, further studies investigated dialog-based interaction between users and AI that is represented as a virtual agent to augment a human-human dialog. For example, Luo et al. (2018) address different learning paradigms to enable AI to make appropriate action suggestions to users. Gao and Jiang (2021) show that the efficiency and partially the effectiveness of users can be increased by AI suggestions in a hybrid conversational system.

Prior work shows that augmentation with HISs can improve the processing of requests in text-based online service encounters by providing information to assist SEs in making decisions and solving problems. However, to date, the focus has been predominantly on the basic design dimensions and technical properties of HISs. To fully leverage the potential of HISs in online service encounters, human-centered design is needed to foster collaboration between AI and SEs.

2.3.3 Human-AI Interaction in Online Service Encounters

The application of AI for the automation and/or augmentation of text-based online service delivery is closely connected to the design of the interaction between humans (SKs and SEs) and AI. Depending on the infusion archetypes, different constellations of the entities SK, SE, and AI are created for service encounters involving users who interact with AI. Following the basic principles of HCI research, the design of interaction involves "understand[ing] and support[ing] human beings interacting with and through technology" (Carroll, 1997, p. 62). To achieve acceptance, usability, and usefulness among users, the development, deployment, and influence of IT (e.g., AI) on users is studied by considering the utilization of information for a specific task (Hevner & Zhang, 2011; Ostrom et al., 2019; W. Xu, 2019). By adopting a human-centered approach, AI's features are adapted to the needs of users (Shneiderman, 2020; W. Xu, 2019).

The existing research shows that the automation and augmentation of text-based service delivery with CAs and HISs that are represented as virtual agents or embedded AI have the potential to optimize service production. Depending on the purpose of the application of these AI-based solutions (automation vs. augmentation), the design of human-AI interaction has been guided by different objectives. The AI-based self-service interaction with CAs has so far been studied with respect to designing humanlike characteristics and behaviors (Gnewuch et al., 2017; Zierau, Wambsganss, et al., 2020). Therefore, research has focused on design aspects that create, inter alia, engaging, pleasant, and goal-directed interactions with these virtual agents. In this context, the influence of social cues on users regarding CAs' interaction styles (e.g., style of messages, dialog management, and degree of (pro)activity) and appearance-related characteristics has been explored (e.g., Diederich et al., 2019; Feine et al., 2019; Gnewuch et al., 2018). However, there is lack of human-centered design knowledge that enables a hybrid form of online service encounters. More precisely, there is a paucity of knowledge regarding how to design CAs in such a way that they are able to support SKs prior to handover and elicit the required information. In addition, design knowledge is needed to create a solution that supports the continuation of SEs' request processing after real-time handovers (Y.-S. Huang & Dootson, 2022; Poser, Hackbarth, & Bittner, 2022; Poser et al., 2021).

To augment online service encounters with AI as part of HISs, the limited existing knowledge of interaction refers to establishing a symbiosis between AI and users. Therefore, the design of dynamic collaboration between AI and users pertains to the processing, analysis, and use of information to achieve a joint task goal. Depending on the form of online service delivery, HISs have been studied to support SEs during real-time interactions with SKs or the delayed, asynchronous processing of SK requests. For asynchronous processing, initial knowledge was generated for the design of an embedded AI with a focus on the characteristics of the information presented (Schmidt et al., 2021). For synchronous processing, initial insights into interaction design for an HIS with embedded AI for chat-based service delivery were provided by Wiethof and Bittner (2022). In this preliminary work, human-centered design aspects that facilitate hybrid collaborative learning while supporting SEs answering SK requests were considered. Therefore, available knowledge on the design of HISs regarding the collaboration between AI and users has so far been limited. To enable hybrid online service encounters using HISs for augmentation, there is a need for human-centered design knowledge that is adapted to the requirements of synchronous, chat-based interactions with SKs and the bounded capabilities of SEs to process information. Accordingly, the input and output formats of AI as part of HISs need to be designed (Keyser et al., 2019; Poser, Wiethof, Banerjee, et al., 2022; Wiethof & Bittner, 2022).

In response to these research gaps, solutions that adapt, complement, and extend CAs and HISs to enable hybrid online service delivery are required. In this context, human-centered knowledge that considers the characteristics of users, systems, and tasks is needed for interaction design (Rzepka & Berger, 2018; Zhang & Li, 2005). For the delivery of intangible services, conditions for co-creation in online encounters should be established (Glushko & Tabas, 2008). As this type of online service delivery is knowledge- and information-intensive, SKs need to be able to describe their requests so that SEs can provide appropriate information, give advice, or solve problems. To achieve a hybridization of automated or augmented online service encounters, AI-based solutions that are represented as virtual agents or embedded in user interfaces should be adapted to the task characteristics and needs of different users. As part of the automation strategies, the nature and structure of interaction should be adapted to the needs of SKs. Consequently, CAs that are represented as virtual agent solutions should be designed to support SKs in providing relevant input to enable handovers from CA to SEs. From the perspective of SEs, interaction with a user interface should help evaluate, analyze, and use information from the previous CA-SK interaction to recover failed automated encounters. As part of the augmentation strategies with HISs, AI represented as a virtual agent or embedded in a user interface should support SEs in online service encounters with complex, dynamic, and synchronous interactions. For the design of interaction with AI, a suitable human-centered format and volume for the presentation of information should be determined, as SEs continuously make decisions to determine how to continue the interaction.

In this dissertation, the knowledge gaps regarding AI-based solutions represented as virtual agents or embedded in a user interface are addressed to identify human-centered knowledge for their design. For this purpose, the HCI framework by Zhang and Li (2005) serves as an orientation to consider the elementary characteristics of human-AI interaction (see Figure

4). For the tasks (automated and augmented) and different users (SE and SK), the interaction with the different representations of AI (AI-enabled virtual agent and embedded AI) should, on the one hand, generate information to prepare required handovers. On the other hand, the presentation of information should serve as support for users, thus reducing the strain of the service encounter.

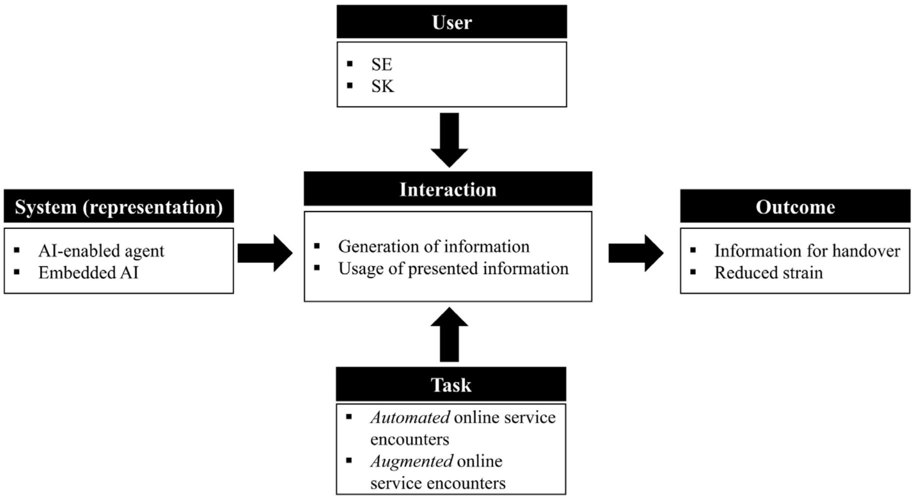

Figure 4. HCI framework with relevant characteristics (Rzepka & Berger, 2018), adapted

3 Research Design

3.1 Research Paradigm

Based on the RG of this thesis, DSR is chosen as an "important and legitimate [...] research paradigm" (Gregor & Hevner, 2013, p. 337) for research in the IS discipline. Rooted in the engineering and sciences of the artificial (Nunamaker et al., 1990; Simon, 1996), DSR represents a "problem-solving paradigm" (Hevner et al., 2004, p. 76). To address practical challenges, design knowledge is generated; it can manifest as artifacts (i.e., constructs, models, methods, and instantiations), design principles (DPs), or design theories (Gregor & Hevner, 2013; Hevner et al., 2004; Jones & Gregor, 2007). While ensuring a high level of rigor, impactful and useful research results can be produced for practice that reduces the relevance problem (Hevner & Chatterjee, 2010; Hevner et al., 2004). Design knowledge that emerges through DSR has a prescriptive nature (what can be) to determine "how things could be and how to achieve the specified ends in an effective manner" (Gregor, 2006; Hevner & Chatterjee, 2010; Iivari, 2007, p. 46). This makes it different from the descriptive and explanatory knowledge (what is) of the natural and social sciences with a descriptive, explanatory, or predictive character (Hevner & Chatterjee, 2010; van Aken, 2004).

According to Hevner (2007), a DSR research project consists of three cycles. Their existence indicates the consideration of a problem class in practice and the use of existing scientific knowledge for the generation of design knowledge (Hevner et al., 2004). The relevance cycle initiates the project by identifying problems and requirements for solutions in the environment. The acceptance of the results is determined by their fitness to solve problems (Hevner, 2007; Venable, 2006; vom Brocke et al., 2020). Through the rigor cycle, justificatory knowledge and methods for deriving and evaluating design knowledge are selected (Baskerville et al., 2018; Hevner et al., 2004; Jones & Gregor, 2007). The reported output of the project contributes to the knowledge base. In the design cycle, design knowledge is generated by executing the core activities of building and evaluating to iteratively evaluate and adapt artifacts (Hevner et al., 2004; March & Smith, 1995).

These three DSR cycles are executed with a set of articles to address the RQs of this thesis (see Section 3.2). In doing so, different epistemological viewpoints are adopted to address the various knowledge interests across the DSR cycles. As epistemological assumptions and methodological approaches mutually influence each other, a mix of methods is applied (Niehaves, 2005) (see Section 3.3). Generally guided by the philosophical foundations of pragmatism, the research endeavor of this dissertation is characterized by activities that aim to produce results with a utility character that are evaluated based on their practical consequences (Hevner & Chatterjee, 2010; Hevner et al., 2004; Venkatesh et al., 2013). In the relevance cycle, the epistemological assumptions of interpretivism are adopted to capture the subjective realities of individuals in socio-technical work systems (Niehaves, 2007). On the one hand, these findings are used to define the problem space. On the other hand, requirements for the generation of design knowledge are collected as goodness criteria (vom Brocke et al., 2020). Epistemological assumptions of positivism are adopted in the rigor and design cycles. Design knowledge of this cumulative dissertation is created, inter alia, through the consideration of existing descriptive knowledge. Moreover, empirical evaluations are conducted to gain insights into the generalizability of the results by producing approximately accurate representations of reality (Weber, 2004).

3.2 Research Strategy

The goal of this cumulative dissertation is to enable hybrid text-based online service delivery by generating design knowledge for the construction of innovative artifact-based solutions and their integration into online service delivery work systems. By focusing on human-centered IS design, contributions at the intersection of DSR and HCI are provided with prescriptive statements and designed entities (Hevner & Zhang, 2011). Guided by the three DSR cycles, these contributions to the human knowledge base and practical environment are accumulated and evolve across several articles (Hevner, 2007). To systematize the procedure of generating and evaluating design knowledge in the thesis and to align it with scholarly standards, the established rigorous rules of DSR are followed (Baskerville et al., 2018; Hevner et al., 2004; vom Brocke et al., 2020). In addition, the steps of normative DSR reference processes are followed and implemented in the articles (Kuechler & Vaishnavi, 2012; Peffers et al., 2007).

Serving the overarching RG, the interconnected articles in this thesis address single or multiple RQs (see Table 2). Poser and Bittner (2021) (**Art. 1**) and Poser, Wiethof, and Bittner (2022) (**Art. 2**) motivate the use of AI that is embedded in user interfaces or represented as a virtual agent to solve existing challenges in online service delivery work systems in practice (RQ 1a). Existing design knowledge and design entities are systematically captured to lay the foundation for potential solutions through Poser and Bittner (2021) (**Art. 1**), Poser, Wiethof, and Bittner (2022) (**Art. 2**), and Poser and Bittner (2020) (**Art. 3**) (RQ 1b). By presenting aspects to consider, along with processual locations for the integration of these AI-based solutions Poser and Bittner (2021) (**Art. 1**) and Poser, Wiethof, and Bittner (2022) (**Art. 2**), prescriptive guidance for establishing hybrid online service delivery is proposed (RQ 2a). Human-centered design knowledge for AI-based solutions is developed to enable hybrid forms of service delivery in consecutive and simultaneous online service encounters (RQ 2b). In consecutive encounters, SK requests are handed over from CA to SE when the CA fails during autonomous processing. Poser et al. (2023) (**Art. 5**) - informed by Poser, Küstermann, et al. (2022) (**Art. 4**) - and Poser et al. (2021) (**Art. 6**) present prototypes and prescriptive statements for designing CA interaction with SK to collect the relevant information items before handover to SE. In Poser et al. (2021) (**Art. 6**), tentative design knowledge for transferring previously collected information for handovers is presented with a proof of concept. Following this, Poser, Hackbarth, and Bittner (2022) (**Art. 7**) present prescriptive knowledge and its prototypical instantiation for a handover user interface that enables the real-time, human-centric presentation of this information. To enable hybrid simultaneous encounters, wherein SEs are augmented by AI during the service encounter, design knowledge and prototypes are presented in Poser, Wiethof, Banerjee, et al. (2022) (**Art. 8**) and Wiethof et al. (2022) (**Art. 9**). In both articles, SEs are presented with knowledge suggestions that match the course of interaction with SKs. While Poser, Wiethof, Banerjee, et al. (2022) (**Art. 8**) focus on an HIS with an embedded AI, Wiethof et al. (2022) (**Art. 9**) introduce an HIS with AI represented as a virtual agent. By means of the respective evaluations in articles (**Art. 4-9**), the effects of the created solutions on task work in online service delivery work systems are assessed (RQ 3a). With respect to RQ 3b, articles (**Art. 1-2; Art. 4-9**) contribute to the knowledge base by presenting validated prescriptive design knowledge and design entities.

Table 2. Contributions of articles to RQs

#	Article	RQs	Contribution to RQs
Art. 1	*Poser & Bittner (2021)*	1a	Identification of SEs' work-related issues in online service delivery
		1b	Recording of state-of-the-art design knowledge and entities of AI solutions for text-based online service delivery
		2a & 3b	Proposal and evaluation of a work process template to integrate AI-enabled virtual agents or embedded AI into an online service delivery work system
Art. 2	*Poser, Wiethof, & Bittner (2022)*	1a	Identification of missing interconnectedness between AI and SEs in online service delivery
		1b	Recording of state-of-the-art design knowledge and entities of AI solutions for text-based online service delivery
		2a & 3b	Proposal and evaluation of design options to integrate AI solutions into an online service delivery work system
Art. 3	*Poser & Bittner (2020)*	1b	Recording of state-of-the-art design knowledge and entities for CAs represented as AI-enabled virtual agents to collaborate with SEs

Art. 4	*Poser, Küstermann, et al. (2022)*	2b, 3a & 3b	Hybrid consecutive encounters	Proposal, instantiation, and evaluation of design knowledge for CAs represented as an AI-enabled virtual agent to prepare handovers to SE
Art. 5	*Poser et al. (2023)*			
Art. 6	*Poser et al. (2021)*			
Art. 7	*Poser, Hackbarth, & Bittner (2022)*			Proposal, instantiation, and evaluation of design knowledge for a handover user interface for SEs
Art. 8	*Poser, Wiethof, Banerjee, et al. (2022)*		Hybrid simultaneous encounters	Proposal, instantiation, and evaluation of design knowledge for an HIS with embedded AI to augment SEs
Art. 9	*Wiethof et al. (2022)*			Proposal, instantiation, and evaluation of design knowledge for an HIS with AI as a virtual agent to augment SEs

The following sections describe the research activities performed along the three DSR cycles to address the RQs (see also Figure 5). In addition, the modes of using and contributing knowledge are explained, contextualized, and illustrated for the cumulative dissertation. In this context, the designation of research activities (A-J) does not indicate a chronological sequence but is used to provide an optimal overview of interdependent activities across the cycles addressed by the different articles.

3.2.1 Relevance Cycle

With the relevance cycle, opportunities and problems are identified in a real-world environment (Hevner et al., 2004; Kuechler & Vaishnavi, 2012; Peffers et al., 2007; vom Brocke et al., 2020) (see Figure 5 | activity A). As application domains are shaped by socio-technical systems (Hevner & Chatterjee, 2010), the description of the problem space should capture how people and/or machines perform tasks in online service delivery work systems. Accordingly, Poser and Bittner (2021) identify work-related problem scenarios in service production by analyzing current labor practices from the perspective of SEs. In addition, Poser, Wiethof, and Bittner (2022) present current deployment scenarios of AI-based solutions for service delivery based on a representative sample of international companies that shows the missing connectedness of AI and SEs in online service encounters. Based on the derivation of this design knowledge for the problem space, the DSR research project is initialized. Besides these insights, the relevance cycle captures requirements from the environment to ensure the purposefulness of emerging solutions (Gregor, 2009; Hevner, 2007) (see Figure 5 | activity B). This information represents the "goodness criteria from the problem space […] to guide a goal-driven search" for suitable solutions (vom Brocke et al., 2020, p. 523). By rigorously gathering requirements from key stakeholders in the environment, the fitness of the emerging design knowledge and tangible artifacts for solving their challenges can be ensured (Gregor & Hevner, 2013; vom Brocke et al., 2020). Therefore, Poser, Wiethof, and Bittner (2022), Poser et al. (2021), Poser et al. (2023), Poser, Hackbarth, and Bittner (2022), and Wiethof et al. (2022) accessed contextual knowledge via the relevance cycle to inform design activities. Collectively, research activities A and B address RQ 1a as part of the relevance cycle.

The goal of DSR projects is to expand organizational and human capabilities in the environment through immediate or future benefits (Österle et al., 2011). To test its effect on the environment, design knowledge and its instantiation are applied and presented to members of the relevant stakeholders (Peffers et al., 2018). Seeking to evaluate fitness for use, Poser et al. (2021), Poser, Hackbarth, and Bittner (2022), Poser, Küstermann, et al. (2022), Poser et al. (2023), Poser, Wiethof, Banerjee, et al. (2022), Wiethof et al. (2022), and Poser, Wiethof, and Bittner (2022) verified the respective artifacts and their outcomes with individuals from the environment (vom Brocke et al., 2020). Thereby, the utility, usefulness, and effectiveness of the artifacts in fulfilling their purpose were assessed (Venable, 2006) (see Figure 5 | activity C). In this context, the effects of the artifacts on the work of SEs were evaluated. Addressing RQ 3a, the output of the DSR project is evaluated and transferred to the environment.

3.2.2 Rigor Cycle

Besides practice-relevant requirements, applicable knowledge should be extracted from the knowledge base to ensure a balance between relevance and rigor in a DSR project. By systematically identifying, considering, and applying existing Ω-knowledge (e.g., descriptive and explanatory), as well as λ-knowledge (i.e., prescriptive) from the knowledge bases, the innovativeness of the project outcome can be ensured (Drechsler & Hevner, 2018; Hevner, 2007; Hevner et al., 2004; Jones & Gregor, 2007). Grounded in the extant literature, in this dissertation, state-of-the-art justificatory knowledge was used to facilitate the understanding of the environmental challenges and classify the practice-based findings. In addition, the state of scientific knowledge on the topic under investigation was reviewed. For this purpose, Poser and Bittner (2020), Poser, Wiethof, and Bittner (2022), and Poser and Bittner (2021) conducted literature analyses to systematically record existing knowledge and artifacts to identify the entry point for the DSR project (see Figure 5 | activity D). Thereby, activity D contributes to RQ 1b. To achieve contributions from design activities, Poser, Wiethof, and Bittner (2022), Poser, Küstermann, et al. (2022), Poser et al. (2023), Poser et al. (2021), and Wiethof et al. (2022) built on existing conceptual and design knowledge (Gregor & Hevner, 2013; vom Brocke et al., 2020). In addition, Poser and Bittner (2021), Poser, Küstermann, et al. (2022), Poser et al. (2023), Poser, Wiethof, and

Bittner (2022), and Wiethof et al. (2022) used kernel theories and theoretical frameworks to consider relevant mechanisms of action as well as established regularities for the creative process of deriving design knowledge (Hevner et al., 2004; Kuechler & Vaishnavi, 2012; Walls et al., 1992). Therefore, activity E refers to RQ 2a and RQ 2b by drawing on knowledge to inform design activities.

As existing knowledge was systematically incorporated through the rigor cycle, the creation of routine design was prevented (Hevner et al., 2004). Therefore, the design knowledge produced by Poser, Wiethof, and Bittner (2022), Poser, Küstermann, et al. (2022), Poser et al. (2023), Poser et al. (2021), Poser, Hackbarth, and Bittner (2022), Poser, Wiethof, Banerjee, et al. (2022), and Wiethof et al. (2022) advances the λ-knowledge base (see Figure 5 | activity F). Thus, RQ 3b is addressed.

3.2.3 Design Cycle

The core activities in DSR projects constitute the iterative production and evaluation of design knowledge in the design cycle (Hevner, 2007). By diligently considering the research opportunity and requirements from the field through the relevance cycle, the design activities in the cumulative dissertation were focused on two topics. On the one hand, design knowledge for the integration of AI-based solutions into work systems for hybrid online service delivery was determined for RQ 2a (see Figure 5 | activity G). Poser, Wiethof, and Bittner (2022) present decision options for embedding AI to facilitate hybrid service delivery. This taxonomy represents an artifact of the type "model" that describes concepts and their relationships in hierarchical and sequential order for its application (Kundisch et al., 2022). On the other hand, in the context of RQ 2b, design knowledge was produced for the construction of AI-based solutions that are represented as a virtual agent or embedded in a user interface to enable hybrid text-based service encounters (see Figure 5 | activity H). With a focus on human-centered design knowledge, prescriptive statements were formulated. Following established DSR procedures, design requirements (also referred to as meta-requirements (MRs)) were identified via insights from practice and by drawing on the knowledge bases (Meth et al., 2015; Möller et al., 2022). Subsequently, following Gregor et al.'s (2020) guidelines, DPs were defined. These principles are established to define prescriptive knowledge and represent "codified, abstracted design knowledge as linguistic statements" (Maedche et al., 2021; Möller et al., 2022, p. 7). In this thesis, DPs, on the one hand, address CAs as AI-enabled virtual agents that, according to their integration point, are oriented toward interaction with SKs (Poser et al., 2023; Poser, Küstermann, et al., 2022; Poser et al., 2021) and SEs (Wiethof et al., 2022). On the other hand, they refer to the design of AI embedded in user interfaces that are used by SEs (Poser, Hackbarth, & Bittner, 2022; Poser, Wiethof, Banerjee, et al., 2022).

As part of the build-and-evaluate activities, the generated design knowledge is operationalized with instantiations. This allows their effectiveness to be demonstrated and validated (Jones & Gregor, 2007; Kuechler & Vaishnavi, 2012; Peffers et al., 2018). For this purpose, Poser, Wiethof, and Bittner (2022) used a table format. For technical artifacts, prototyping is an established procedure used in DSR (Baskerville et al., 2009; Jones & Gregor, 2007; Mason & Carey, 1983). To account for the challenges of output variability and the evolving characteristics of AI-based solutions in determining interaction design, different types of prototypes were developed in the articles (Yang et al., 2020). In the early stages, prototypes were realized as proof of concepts and proof of applicability (e.g., rule-based simulator and mixed fidelity prototype) (Poser, Hackbarth, & Bittner, 2022; Poser et al., 2021; Wiethof et al., 2022). For fully functioning solutions in Poser, Küstermann, et al. (2022), Poser et al. (2023), and Poser, Wiethof, Banerjee, et al. (2022), prototypes were produced with different user interfaces generating probabilistic adaptive outputs.

To ensure the viability of the DSR project outcomes, evaluation activities focusing on the integration (RQ 2a) and design of solutions (RQ 2b) were conducted (see Figure 5 | activity I & J). Informed via the rigor cycle, evaluation patterns and appropriate methods were identified for this purpose. Aiming to assess whether the instantiated design knowledge achieves utility in addressing the real-world challenge, several attributes were evaluated at different time points (Venable et al., 2016). Poser, Küstermann, et al. (202), Poser et al. (2023), Poser, Wiethof, and Bittner (2022), and Poser, Hackbarth, and Bittner (2022) evaluated the completeness, operationality, and feasibility of design knowledge ex-ante. In Poser, Wiethof, and Bittner (2022), Poser, Küstermann, et al. (2022), Poser et al. (2023), Poser et al. (2021), Poser, Hackbarth, and Bittner (2022), Poser, Wiethof, Banerjee, et al. (2022), and Wiethof et al. (2022), the applicability, effectiveness, efficiency, and usefulness of expository instantiations of design knowledge were assessed ex-post (Pries-Heje et al., 2008; Sonnenberg & vom Brocke, 2012). These activities represent semi-naturalistic approaches, as evaluations were conducted with relevant target groups from or in the environment in standardized settings (e.g., focus groups and user tests).

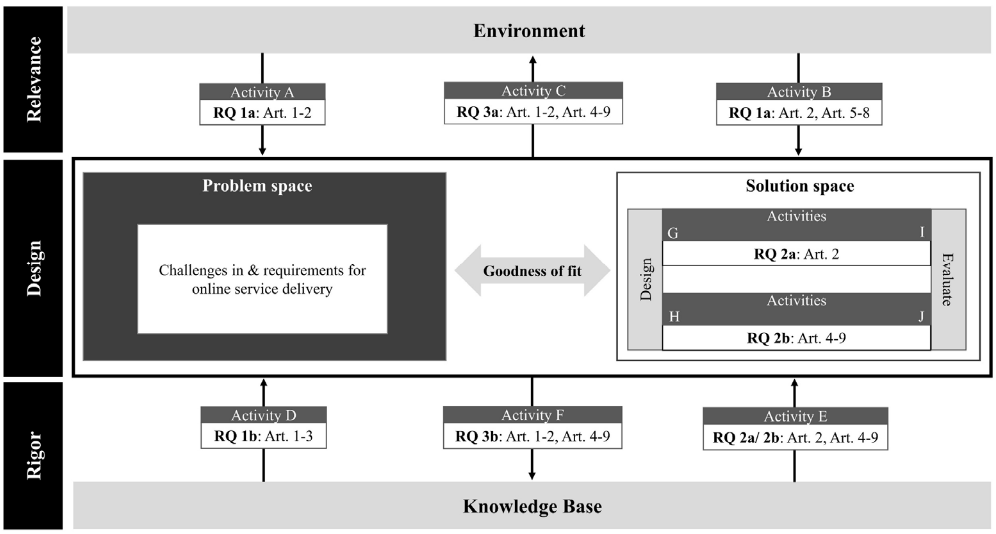

Figure 5. Research activities performed across DSR cycles

3.2.4 Knowledge Utilization and Contribution

The performed research activities (A-J) encapsulate an iterative, cyclical search process for solutions in the solution space to approach the challenge from the environment in the problem space. This process involved several knowledge paths to strategically use, produce, and contribute Ω-knowledge and λ-knowledge (Drechsler & Hevner, 2018; Gregor & Hevner, 2013; vom Brocke et al., 2020) (see Figure 6).

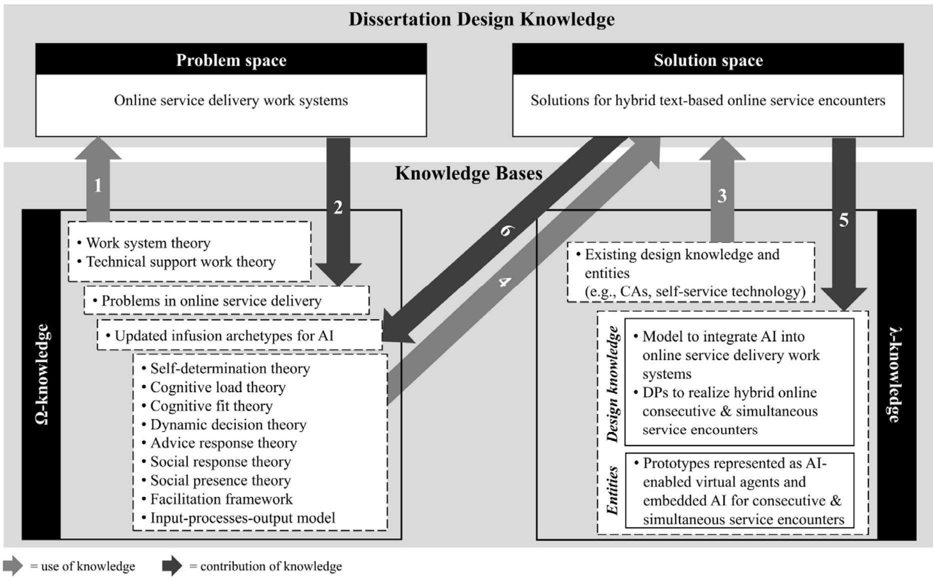

Figure 6. Paths for the utilization and contribution of different knowledge types

With the intention of ensuring the projectability of the emerging design knowledge, a practical challenge in the environment that exists in related application domains was addressed (Baskerville & Pries-Heje, 2019; vom Brocke et al., 2020). For research activity A (path 1 - use Ω), sense-making in two online service delivery work systems (customer service and internal IT support) was performed. Drawing on insights from work system theory (Alter, 2013) and technical support work theory (Das, 2003), existing Ω-knowledge was applied. Based on inductive data collection procedures in the environment, research activity A (path 2 - contribute Ω) uncovered existing problems in processes and activities for text-based online service delivery. As part of activity F, these insights are contributed as Ω-knowledge.

Based on these challenges, design knowledge in the form of DPs and an abstract model, as well as entities, were created in the solution space for the purposeful integration and use of AI. In doing so, the existing limitations of CAs and HISs were considered and the potential of hybrid constellations comprising these systems and SEs were exploited. Through research activity E (path 3 - use λ), the generation of the model, design requirements, and DPs was grounded in λ-knowledge comprising suitable theories and design entities. In addition, (path 4 - use Ω) Ω-knowledge was considered as a lens through which to derive design requirements or formulate them based on theoretical insights. Therefore, applicable theories were used to create human-centered DPs and entities. In this regard, theoretical insights related to human needs at work (self-determination theory) (Deci & Ryan, 2008), information processing (cognitive load theory, cognitive fit theory) (Sweller, 1988; Vessey & Galletta, 1991), decision-making behavior (dynamic decision theory, advice response theory) (Edwards, 1962), forms of collaboration (facilitation framework, input-process-output model) (Bostrom et al., 1993; Kozlowski & Bell, 2003), and the application of social rules (social response theory, social presence theory) (Gefen & Straub, 1997; Nass & Moon, 2000; Short et al., 1976) were considered.

Research activities F-J cover the production and evaluation of the solutions in this dissertation. Two forms of contribution are achieved in the λ-knowledge base (path 5 - contribute λ). First, prescriptive knowledge consisting of a model and design requirements and DPs for design and action emerged (Gregor et al., 2020). Second, solution artifacts in the form of a taxonomy and prototypes were created. In addition, as part of activities G and I, a contribution to the understanding of the role of AI in online service encounters has emerged through the expansion of existing infusion archetypes for the integration of AI into online service delivery work systems (path 6 – contribute Ω).

3.3 Research Methods

For this cumulative dissertation, different research methods are used to identify practical problems, research gaps, and derive and evaluate design knowledge and its situated implementations. Following advocates of methodological pluralism, a mixed-methods approach is applied (Mingers, 2001; Niehaves, 2005; Venkatesh et al., 2016). By purposefully combining philosophical traditions and methods, the aim is to maximize the knowledge contribution and account for the complexity and multiphase nature of this dissertation (Mingers, 2001). In the following subsections, the applied methods are defined and described.

3.3.1 Literature Review

Conducting literature reviews enables the advancement of knowledge in continuously evolving and maturing research fields (Paré et al., 2015; Webster & Watson, 2002). By analyzing, synthesizing, and integrating the extant literature on a topic of interest, the state of knowledge is captured and topics for future research identified (Templier & Paré, 2015; vom Brocke et al., 2015). Based on summaries and descriptions of content, relevant prior work (e.g., theories, artifacts, and methodological approaches) can be considered (Drechsler & Hevner, 2018; Gregor & Hevner, 2013; vom Brocke et al., 2020). By grounding research projects in the existing knowledge and addressing essential knowledge gaps, substantial contributions can be made (Hevner, 2007).

Serving different objectives, three types of literature reviews introduced by Okoli (2015) were applied in this thesis. A *thesis literature review* was conducted to derive the motivation and research objective and to provide a comprehensive review of the literature relevant to the research topic (see Sections 1 & 2). Furthermore, reviews were performed on the *theoretical background* of the articles in this cumulative dissertation. These reviews served to carve out the addressed problems and present previous work for each article, derive the objectives of a solution (Poser, Küstermann, et al., 2022; Poser et al., 2021; Wiethof et al., 2022), and adopt the conceptual approach for the development of a taxonomy (Poser, Wiethof, & Bittner, 2022). A *stand-alone literature review* was completed by analyzing and organizing publications and their contributions using a concept-centric approach to present the core findings (Webster & Watson, 2002). Adhering to their core characteristics, Poser and Bittner (2020), Poser, Wiethof, and Bittner (2022), and Poser and Bittner (2021) present structured literature reviews. The reviews present an overview of knowledge by combining insights from various fields that were obtained using different research methodologies. To position the research project of this cumulative dissertation, well-established methods were used to ensure the reliability, validity, and objectivity of the process (Cooper, 1988; Levy & J. Ellis, 2006; vom Brocke et al., 2015; vom Brocke et al., 2009; Wolfswinkel et al., 2013).

3.3.2 Taxonomy Development

Taxonomies help consolidate the understanding and further sense-making of concepts and knowledge in complex research fields. By means of classification, existing knowledge is organized in a process and/or represented as a result of it (Bailey, 1994; Nickerson et al., 2013). The knowledge is presented by identifying relevant dimensions and corresponding characteristics (Kundisch et al., 2022; Szopinski et al., 2019). The systematic structure of taxonomies shows the relationships, commonalities, and differences between objects of interest (Glass & Vessey, 1995).

As part of this cumulative dissertation, a taxonomy was produced (Poser, Wiethof, & Bittner, 2022). For the development process, Nickerson et al.'s method (2013), which is established in IS research, was applied (Kundisch et al., 2022; Oberländer et al., 2019). In addition, to ensure rigorous development and evaluation, Kundisch et al.'s (2022) methodological guidelines were consulted. To capture the current state of knowledge in a holistic format, several iterations are performed during taxonomy development using the conceptual-to-empirical approach, the empirical-to-conceptual approach, or both. (Nickerson et al., 2013). In Poser, Wiethof, and Bittner (2022), on the one hand, the existing scientific knowledge was systematically searched and considered using the conceptual-to-empirical approach. On the other hand, findings from practice were examined by adopting the empirical-to-conceptual approach. These findings were summarized in terms of characteristics and dimensions by applying methods for qualitative analyses (Kundisch et al., 2022). Following scientific recommendations, two evaluation activities were performed to analyze the qualitative and quantitative data to ensure the usefulness, applicability, validity, and usability of the resulting taxonomy (Kundisch et al., 2022; Szopinski et al., 2019).

3.3.3 Qualitative Data Collection and Analysis

Qualitative research methods are used to capture people's subjective meanings, experiences, and actions (Fossey et al., 2002; Miles & Huberman, 1994). This involves sampling information sources (e.g., people and different types of data) to obtain qualitative data. By using adequate qualitative methods (e.g., interviews, focus groups, and document collection) to acquire appropriate data, rigorous qualitative studies can be conducted (Maxwell, 1992; Venkatesh et al., 2013). In IS research, subjective knowledge is obtained using different qualitative methods to capture the realities of people in their social context and to engage them in the derivation of constructive knowledge (Goldkuhl, 2012; Lee & Hubona, 2009). In addition, the collection of qualitative data enable the evaluation of IS artifacts (Prat et al., 2015; Venable et al., 2016).

In this thesis, qualitative data were collected via different methods to consider practical problems and requirements to identify possible solutions. The utility of emergent design knowledge and artifacts can thereby be ensured (Hevner et al., 2004). Semi-structured interviews were used because they represent an established question-based method in the IS discipline. With the help of interview guidelines comprising open-ended questions, relevant topics were covered, and the interviewees were given the flexibility to elaborate on certain aspects (Myers & Newman, 2007). To identify issues, elicit requirements from various stakeholders, and perform summative ex-post evaluations of the resulting artifacts, several sets of semi-structured interviews were conducted with the appropriate participants (Poser & Bittner, 2021; Poser, Hackbarth, & Bittner, 2022; Poser et al., 2023; Poser, Küstermann, et al., 2022; Poser et al., 2021; Poser, Wiethof, Banerjee, et al., 2022; Wiethof et al., 2022). To conduct the ex-ante evaluation of an artifact, a focus group was used (Poser, Küstermann, et al., 2022). Following Tremblay et al.'s (2010) guidelines for exploratory focus groups, a formative evaluation was performed. The group discussion of participants was facilitated by using guiding questions to obtain a rich set of data to improve an artifact under construction. To supplement the other types of qualitative data, different types of documents were collected to sample additional information (e.g., process documentation and reports) (Poser & Bittner, 2021; Poser, Wiethof, & Bittner, 2022).

Qualitative analysis is used to describe and/or explicate what is being studied by synthesizing, summarizing, interpreting, and sorting extensive datasets (Conboy et al., 2012; Miles & Huberman, 1994). The qualitative data collected as part of this cumulative dissertation were analyzed using the qualitative content analysis approach (Mayring, 2014). Following a mix of inductive (based on available data) and deductive (based on theoretical findings) analysis procedures, the qualitative data were coded according to Saldaña (2013), where appropriate in several cycles with different strategies, to establish a category system (Mayring, 2014). Based on these analyses, problems in practice could be systematically identified, requirements for artifacts could be derived to infer design knowledge, and artifact evaluation could be presented.

3.3.4 Quantitative Data Collection and Analysis

Number-based quantitative data can be used to measure study objects and to examine the relationship between their quantifiable properties. The data are collected using a variety of methods to document observations and are analyzed via descriptive and inferential statistical procedures. In IS research, the application of quantitative methods for data collection and analysis is, inter alia, used for ex-ante and ex-post evaluations of artifacts in natural and artificial contexts (Prat et al., 2015; Pries-Heje et al., 2008; Venable et al., 2016).

As part of this thesis, primary (e.g., perceptions and experiences of participants) and secondary (e.g., system data through the use of artifacts) quantitative data were collected to evaluate the utility and quality of constructed artifacts (Hevner et al., 2004). The data were collected via standardized experiments, user tests, and questionnaires (Pries-Heje et al., 2008). In semi-naturalistic evaluation settings, system usage data from users were gathered and summarized using descriptive statistics (e.g., mean, median, and standard deviation) (Poser, Hackbarth, & Bittner, 2022; Poser, Küstermann, et al., 2022; Poser, Wiethof, Banerjee, et al., 2022). Online questionnaires were designed and administered to elicit the influence of artifacts on individuals and their contexts. By creating latent variables via literature-based operationalizations (e.g., perceived ease of use and perceived usefulness) data about participants' perceptions were obtained (Siau & Rossi, 2011). These measurements were analyzed using two procedures: the data were presented by applying descriptive statistics methods (Poser et al., 2023; Poser, Wiethof, & Bittner, 2022; Wiethof et al., 2022), and inferential statistics methods were used (nonparametric test method) to test comparisons between different properties of systems (Poser, Küstermann, et al., 2022).

4 Publications

4.1 Related Publications

In this cumulative dissertation, 13 articles have been created that are directly or indirectly related to the addressed research topic. All articles were submitted to reputable and peer reviewed IS conferences and a journal. Tables 3 and 4 present these articles chronologically according to their publication date and subdivided by the type of outlet (articles with * are included in the dissertation).

Table 3. Journal article

Journal Article
* Poser, M., Küstermann, G. C., Tavanapour, N., & Bittner, E. A. C. (2022). *Design and Evaluation of a Conversational Agent for Facilitating Idea Generation in Organizational Innovation Processes*. Information Systems Frontiers, 24(3), 1-26.

Table 4. Conference articles

Conference Article
Tavanapour, N., Poser, M., & Bittner, E. A. C. (2019). *Supporting the Idea Generation Process in Citizen Participation – Toward an Interactive System with a Conversational Agent as Facilitator.* European Conference on Information Systems (ECIS). Stockholm-Uppsala, Sweden.
* Poser, M., & Bittner, E. A. C. (2020). *Hybrid Teamwork: Consideration of Teamwork Concepts to Reach Naturalistic Interaction between Humans and Conversational Agents.* International Conference on Wirtschaftsinformatik (WI). Potsdam, Germany.
* Poser, M., Singh, S., & Bittner, E. A. C. (2021). *Hybrid Service Recovery: Design for Seamless Inquiry Handovers between Conversational Agents and Human Service Agents.* Hawaii International Conference on System Sciences (HICSS). Virtual Conference.
* Poser, M., & Bittner, E. A. C. (2021). *(Re)Designing IT Support: How Embedded and Conversational AI Can Augment Technical Support Work.* International Conference on Information Systems (ICIS). Austin, TX, USA.
* Poser, M., Wiethof, C., Banerjee, D., Subramanian, V. S., Paucar, R., & Bittner, E. A. C. (2022). *Let's Team Up with AI! Toward a Hybrid Intelligence System for Online Customer Service.*

International Conference on Design Science Research in Information Systems and Technology (DESRIST). St. Petersburg, FL, USA.
* Poser, M., Wiethof, C., & Bittner, E. A. C. (2022). *Integration of AI into Customer Service: A Taxonomy to Inform Design Decisions.* European Conference on Information Systems (ECIS). Timișoara, Romania.
* Poser, M., Hackbarth, T., & Bittner, E. A. C. (2022). *Don't Throw It Over the Fence! Toward Effective Handover from Conversational Agents to Service Employees.* International Conference on Human-Computer Interaction (HCII). Virtual Conference.
* Wiethof, C., Poser, M., & Bittner, E. A. C. (2022). *Design and Evaluation of an Employee-Facing Conversational Agent in Online Customer Service.* Pacific Asia Conference on Information Systems (PACIS). Virtual Conference.
Li, M. M., Peters, C., Poser, M., Eilers, K., & Elshan, E. (2022). *ICT-enabled Job Crafting: How Business Unit Developers Use Lowcode Development Platforms to Craft Jobs*. International Conference on Information Systems (ICIS). Copenhagen, Denmark.
Lewandowski, T., Poser, M., Kučević, E., Heuer, M., Hellmich, J., Raykhlin, M., Blum, S., & Böhmann, T. (2023). *Leveraging the Potential of Conversational Agents: Quality Criteria for the Continuous Evaluation and Improvement.* Hawaii International Conference on System Sciences (HICSS). Maui, HI, USA.
Banerjee, D., Poser, M., Wiethof, C., Subramanian, V. S., Paucar, R., Bittner, E. A. C., Biemann, C. (2023). *A System for Human-AI Collaboration for Online Customer Support.* AAAI Conference on Artificial Intelligence. Washington, DC, USA.
* Poser, M., Hörhold, H. K., & Bittner, E. A. C. (2023). *May the Guide Be with You: CA-facilitated Information Elicitation to Prevent Service Failure.* European Conference on Information Systems (ECIS). Kristiansand, Norway.

4.2 Included Publications

To address the RG and RQs of this cumulative dissertation, the thesis includes nine of the 13 articles listed above (see Sections 9 to 17). Tables 5 to 13 each present a summary of these articles, including information about the authors, article type, and outlet (conference track or special issue), as well as, the ranking, methodology, research aim, research contribution, and co-author contribution. The order of the tables and the presentation of the articles in the sections are based on their contribution to the chronologically addressed RQs. The articles were reproduced verbatim with their content, references, and appendix. To ensure the consistent appearance of this dissertation, the articles have been reformatted.

Section 9

Table 5. First article of the cumulative dissertation

Citation	Poser, M., & Bittner, E. A. C. (2021). (Re)Designing IT Support: How Embedded and Conversational AI Can Augment Technical Support Work. In *42nd International Conference on Information Systems (ICIS)*, Austin, TX, USA.
Ranking	VBH-JOURQUAL3: A WKWI: A CORE2018: A*
Article type	*Conference*: Completed Research Paper
Track	IS and the Future of Work
Research aim	As current AI solutions cannot fully substitute for SEs and greater effects are achieved with hybrid service delivery, this article aims to propose a hybrid division of tasks in redefined work processes for information-rich and time-critical online service contexts. Using internal IT support as an example, existing problems in work practices are identified from the perspective of operational units (as-is situation). Adopting a socio-technical approach, the work organization is redesigned and existing problems alleviated by integrating AI-based solutions (to-be solution).
Methodology	DSR, literature review, cross-sectional qualitative field study via semi-structured interviews
Research contribution	The article contributes to research about future-oriented work settings with validated insights into current work processes, work-related issues, and the presentation of hybrid work processes for internal online IT support. Utilizing insights from a cross-sectional qualitative field study, the article contributes a representation of the problem space by locating work-related problems across tasks and process stages. By drawing on insights from research, possible solutions in the form of AI-based agents and embedded AI and their integration into a hybrid work process are presented. A topic for future research is proposed: the interlocking of human and AI activities should be intensified (e.g., handover and presentation of information) to enable streamlined hybrid service delivery processes.
Co-author's contribution	Eva Bittner co-authored this article. She gave overall feedback and edited the article.

Section 10

Table 6. Second article of the cumulative dissertation

Citation	Poser, M., Wiethof, C., & Bittner, E. A. C. (2022). Integration of AI into Customer Service: A Taxonomy to Inform Design Decisions. In *30th European Conference on Information Systems (ECIS)*, Timişoara, Romania.
Ranking	VBH-JOURQUAL3: B WKWI: A CORE2018: A
Article type	*Conference*: Completed Research Paper
Track	Artificial Intelligence in IS Research and Practice
Research aim	The objective of this article is the derivation of design options for the integration of AI into the socio-technical work system online customer service. Therefore, existing knowledge in research and practice regarding the role of AI and its application in customer service is analyzed and systematized.
Methodology	DSR, taxonomy development, qualitative analysis of AI market solutions and companies' service channels, literature review, mixed-method questionnaire, semi-structured interviews, illustrative scenario
Research contribution	The article contributes to an enhanced understanding of AI-based online customer service delivery by presenting a taxonomy. The classification and structuring of AI characteristics can serve to systematically analyze existing AI solutions or make design decisions before development. By adopting a socio-technical perspective, the roles, constellations, and interrelationships of AI, customers, and SEs were addressed. Based on these insights, existing infusion archetypes for AI integration into online customer service were validated and extended.
Co-authors' contribution	Christina Wiethof and Eva Bittner co-authored this article. Christina Wiethof performed the quantitative data analysis of the ex-post evaluation and contributed to Sections 1 and 6. Eva Bittner provided overall feedback. The following aspects were performed in cooperation with Christina Wiethof: development of the idea for the article, creation and analysis of the database, authoring of Section 5, and implementation of the evaluation steps.

Section 11

Table 7. Third article of the cumulative dissertation

Citation	Poser, M., & Bittner, E. A. C. (2020). Hybrid Teamwork: Consideration of Teamwork Concepts to Reach Naturalistic Interaction between Humans and Conversational Agents. In *15th International Conference on Wirtschaftsinformatik (WI),* Potsdam, Germany.
Ranking	VBH-JOURQUAL3: C WKWI: A CORE2018: C
Article type	*Conference*: Completed Research Paper
Track	AI-Based Systems - User Interaction, Design & Methods
Research aim	Hybrid work settings involving CAs are gaining momentum. To enable joint task work between humans and CAs, CAs should act according to their role in a hybrid team. This article aims to consolidate and systemize the state of scientific knowledge on human-centered design knowledge for CAs that builds on psychological constructs.
Methodology	Literature review
Research contribution	The article provides a systematic overview of previous work on CAs by mapping it to established psychological constructs from team research. The in-depth analysis of 19 publications demonstrates that studies with a conceptual focus and instantiated CAs are primarily concerned with task-related constructs, while mostly disregarding relationship-related constructs. The article contributes to research by making teamwork-specific psychological constructs from team research accessible and usable for IS researchers. Furthermore, avenues for future research are presented: To promote hybrid task work between humans and CAs, a task-based division with reciprocal handovers is proposed. In addition, multiple task- and relationship-related behaviors should be included in human-centric designs of CAs.
Co-author's contribution	Eva Bittner co-authored this article. She advised on the conceptual approach and gave overall feedback.

Section 12

Table 8. Fourth article of the cumulative dissertation

Citation	Poser, M., Küstermann, G. C., Tavanapour, N., & Bittner, E. A. C. (2022). Design and Evaluation of a Conversational Agent for Facilitating Idea Generation in Organizational Innovation Processes. *Information Systems Frontiers*, *24*(3), 771–796. https://doi.org/10.1007/s10796-022-10265-6
Ranking	VBH-JOURQUAL3: B WKWI: A CORE2018: A
Article type	*Journal*: Completed Research Paper
Special issue	Designing and Managing Human-AI Interactions
Research aim	The objective of this article is to investigate how CAs can be used in semi-automated task settings in such a way that their activities support subsequent human task processing. Using organizational open innovation initiatives as an example, a design for CAs is developed to assist users in generating elaborate textual submissions that meet employees' demands to effectively continue the task. The facilitation concept is applied to structure the dyadic CA-user interaction and provide an engaging submission process.
Methodology	DSR, literature review, exploratory focus groups, semi-structured interviews, computerized linguistic analysis, quantitative questionnaire
Research contribution	This article presents MRs and DPs, as well as an instantiated CA-based facilitator that is capable of guiding users through a submission process. The results of the ex-post evaluation suggest that the facilitated and structured process is engaging and yields well-structured and -elaborated submissions. With this article, a blueprint for the application of the facilitation concept in CAs is provided to achieve one-to-one support of users in creating textual submissions. The article contributes to research on the design of CAs in hybrid work settings. The design knowledge can be applied in related domains (e.g., online service delivery) that rely on substantive textual input.
Co-authors' contribution	Gerrit Küstermann, Navid Tavanapour, and Eva Bittner co-authored this article. Gerrit Küstermann conceptualized and conducted the evaluation of submission texts and the process. He contributed to Sections 1, 6, 7, and 8. Navid Tavanapour contributed knowledge on CA facilitation (e.g., design cycle two) and provided part of the database for the ex-ante evaluation. Eva Bittner contributed to the idea of the article and provided overall feedback.

Section 13

Table 9. Fifth article of the cumulative dissertation

Citation	Poser, M., Hörhold, H. K., & Bittner, E. A. C. (2023). May the Guide Be with You: CA-facilitated Information Elicitation to Prevent Service Failure. In *31st European Conference on Information Systems (ECIS)*, Kristiansand, Norway.
Ranking	VBH-JOURQUAL3: B WKWI: A CORE2018: A
Article type	*Conference*: Completed Research Paper
Track	Design Research and Methods in Information Systems
Research aim	To avert imminent service failures caused by CAs, online service delivery activities of CAs and SEs should be interconnected by a handover of request. The goal of this article is to investigate how CAs can obtain relevant information from SKs in the service encounter to hand it over to SEs. Based on Poser, Küstermann, et al. (2022), design knowledge is evolved by considering the requirements of SKs concerning the interaction with the CA and of SEs regarding the characteristics of information.
Methodology	DSR, semi-structured interviews, quantitative questionnaire
Research contribution	By using and evolving design knowledge from Poser, Küstermann, et al. (2022), prescriptive knowledge with MRs and DPs as well as an instantiated CA is presented. To enable CAs to elicit information from SKs, a service script was created by applying the facilitation concept to design the self-service interaction. The results of two evaluation episodes suggest that with regard to disclosing information, SKs feel supported by the CA, which results in elaborate input for subsequent processing by SEs after handover. The article contributes to research on CAs, hybrid online service delivery, and the future of work scenarios. The generated design knowledge can be used to strengthen the robustness of CA-based service delivery in different online service contexts.
Co-authors' contribution	Hauke Hörhold and Eva Bittner co-authored this article. Hauke Hörhold provided qualitative data and assisted in developing the prototype. Eva Bittner provided overall feedback.

Section 14

Table 10. Sixth article of the cumulative dissertation

Citation	Poser, M., Singh, S., & Bittner, E. A. C. (2021). Hybrid Service Recovery: Design for Seamless Inquiry Handovers between Conversational Agents and Human Service Agents. In *54th Hawaii International Conference on System Sciences (HICSS)*, Virtual conference.
Ranking	VBH-JOURQUAL3: C WKWI: B CORE2018: A
Article type	*Conference*: Completed Research Paper
Track	Decision Analytics and Service Science
Research aim	In this article, a hybrid service recovery strategy for online customer service with real-time handovers from CAs to SEs is investigated. To avert service failures via handover, requirements for the collection and transfer of information and relevant service process steps are explored. The objective of this article is to enable hybrid online service delivery by interconnecting the service delivery activities of CAs and SEs with a transfer of information.
Methodology	DSR, literature review, semi-structured interviews
Research contribution	By considering, the socio-technical interplay of technology, processes, and humans (SEs and customers), the article presents initial, tentative prescriptive design knowledge in the form of MRs and DPs to build real-time handovers. As the first cycle of a larger DSR project, a mixed-fidelity prototype and a process modulation are evaluated to provide a proof of concept. The results can be used to optimize the interlocking of CAs' and SEs' activities in delivering online service. The article contributes to research on CAs and the hybridization of online service delivery processes.
Co-authors' contribution	Sukhpreet Singh and Eva Bittner co-authored this article. Sukhpreet Singh conducted expert interviews and assisted in developing the prototype. Eva Bittner provided overall feedback.

Section 15

Table 11. Seventh article of the cumulative dissertation

Citation	Poser, M., Hackbarth, T., & Bittner, E. A. C. (2022). Don't Throw It Over the Fence! Toward Effective Handover from Conversational Agents to Service Employees. In M. Kurosu (Ed.), *Lecture Notes in Computer Science. Human-Computer Interaction. User Experience and Behavior* (Vol. 13304, pp. 531–545). Springer International Publishing. https://doi.org/10.1007/978-3-031-05412-9_36
Ranking	VBH-JOURQUAL3: C WKWI: B CORE2018: -
Article type	*Conference*: Completed Research Paper
Track	Human-Computer Interaction
Research aim	In continuation to Poser et al. (2021), the goal of this article is to advance the hybrid service recovery strategy involving chat-based handovers from CAs to SEs. As these real-time handovers place high demands on SEs, the article focuses on their perspective of the conditions for the implementation of the strategy. Relevant information types from the preceding CA-customer interaction are identified to support SEs in continuing request processing after handover. In this context, the volume and presentation format of information are investigated to account for SEs' limited cognitive capacities for information processing.
Methodology	DSR, semi-structured interviews, quantitative analysis of usage data
Research contribution	By drawing on theoretical and practice-based insights, the article presents prescriptive design knowledge (MRs and DPs) and a web-based prototype for processing handovers and averting imminent CA failure in online customer service. The results of the conducted evaluation activities suggest that the information presented in the user interface induces a balanced cognitive load in SEs and facilitates the formation of a mental representation of the customer request. The support during service recovery allows SEs to quickly and effortlessly continue request processing after handover. The article contributes to research on hybrid online service delivery and hybrid service recovery strategies.
Co-authors' contribution	Talissa Hackbarth and Eva Bittner co-authored this article. Talissa Hackbarth provided qualitative data for the derivation of MRs. Eva Bittner provided overall feedback.

Section 16

Table 12. Eighth article of the cumulative dissertation

Citation	Poser, M., Wiethof, C., Banerjee, D., Subramanian, V. S., Paucar, R., & Bittner, E. A. C. (2022). Let's Team Up with AI! Toward a Hybrid Intelligence System for Online Customer Service. In A. Drechsler, A. Gerber, & A. Hevner (Eds.), *Lecture Notes in Computer Science. The Transdisciplinary Reach of Design Science Research* (Vol. 13229, pp. 142–153). Springer International Publishing. https://doi.org/10.1007/978-3-031-06516-3_11 **Awarded "Vinton G. Cerf Best Student Paper"**
Ranking	VBH-JOURQUAL3: C WKWI: B CORE2018: A
Article type	*Conference*: Completed Research Paper
Track	Intelligent Systems and HCI
Research aim	In this article, the aim is to apply the hybrid intelligence concept in the context of online customer service. To achieve mutual augmentation between AI and SE, factors that ensure task mastery for SEs are investigated. A human-centric approach is used to generate a design for HISs to augment real-time decision-making in chat-based online service encounters.
Methodology	DSR, semi-structured interviews, quantitative analysis of usage data
Research contribution	The article presents prescriptive design knowledge (MRs and DPs) and an instantiated HIS. Drawing on kernel theories, the derived DPs address three human basic needs for optimal task performance. The results of the user tests demonstrate that the HIS with an embedded AI enables SEs' task mastery and elevates their decision-making behavior. The article contributes to research on hybrid intelligence and online customer service by taking a human-centric approach to adopting an augmentation strategy with HISs.
Co-authors' contribution	Christina Wiethof, Debayan Banerjee, Varun Subramanian, Richard Paucar, and Eva Bittner co-authored this article. Christina Wiethof contributed to the scientific contextualization, created the dataset for the AI component, coordinated the evaluation, and authored Section 6. Debayan Banerjee and Varun Subramanian developed the back end of the HIS prototype. Richard Paucar developed the front end. Eva Bittner provided overall feedback. The following activities were realized in cooperation with Christina Wiethof: development of the idea for the article, conception and implementation of the evaluation strategy, and project management and conceptual guidance of the development team.

Section 17

Table 13. Ninth article of the cumulative dissertation

Citation	Wiethof, C., Poser, M., & Bittner, E. A. C. (2022). Design and Evaluation of an Employee-Facing Conversational Agent in Online Customer Service. In *Pacific Asia Conference on Information Systems (PACIS),* Virtual conference.
Ranking	VBH-JOURQUAL3: C WKWI: B CORE2018: A
Article type	*Conference*: Completed Research Paper
Track	Service Science and IS
Research aim	The hybrid intelligence concept is applied in online customer service to investigate an HIS comprising AI represented as a virtual agent. The objective of the article is to achieve a human-centered augmentation between AI and SE during customer encounters. To allow humanlike collaboration, the derivation of design knowledge for an SE-facing CA is informed by insights from team research.
Methodology	DSR, semi-structured interviews, literature review, quantitative questionnaire, quantitative analysis of usage data
Research contribution	The article presents prescriptive design knowledge in the form of MRs, DPs, and an instantiated SE-facing CA prototype in an HIS. The analysis of the evaluation data shows that the HIS with a virtual agent as AI supported SEs in efficiently solving requests in real-time customer encounters. As SEs showed a strong intention to work with a virtual agent in an HIS, future research can adopt and continue the investigation of hybrid teamwork between CA and SE. The article contributes to research on hybrid intelligence, CAs, and online customer service by offering a solution to fulfill the demands for efficiency (automation) and personalization (human touch) for online service delivery.
Co-authors' contribution	Christina Wiethof and Eva Bittner co-authored this article. Christina Wiethof supported the scientific contextualization, derivation of the design knowledge, and analysis of the qualitative and quantitative data. Christina Wiethof contributed by authoring Sections 2, 6, and 7. Eva Bittner provided overall feedback. The following activities were realized in cooperation with Christina Wiethof: development of the idea for the article, definition of the research design, conception of the evaluation strategy, conceptual responsibility for the prototype development, and authoring Sections 1 and 4.

5 Theoretical Contributions

This section summarizes the theoretical contributions that emerged from the DSR project activities in this cumulative dissertation. The presentation of the content is based on Figure 7, which integrates the structural aspects of online service delivery work systems with the core factors that have an impact on interaction design (Alter, 2013; Rzepka & Berger, 2018; Zhang & Li, 2005). First, the restructuring of processes and activities in work systems for the integration of AI for the delivery of text-based online services is delineated (see Section 5.1). Second, design knowledge and entities for AI-based solutions are presented to enable hybrid online service delivery (see Section 5.2). Third, the individual contributions are classified in relation to the RG, and their overall implications are described (see Section 5.3).

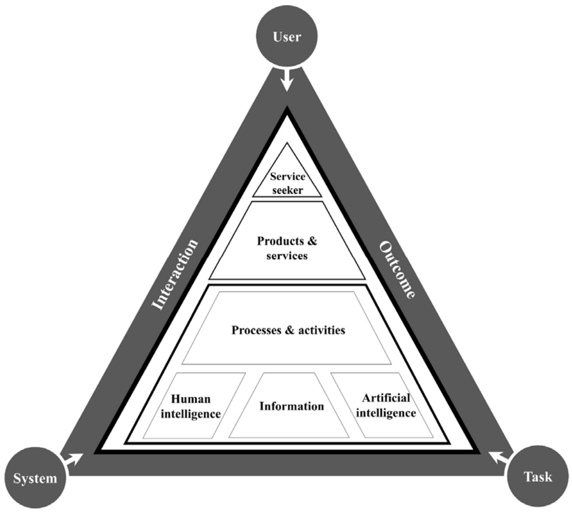

Figure 7. Aspects and factors for the integration and design of AI-based solutions

5.1 Online Service Delivery Work System

With reference to the work system concept (Alter, 2013), the interplay of structural elements for the integration of AI to implement online service encounters is addressed (see Figure 7).

The existing body of literature reveals the increasing importance of online services with text-based chat encounters (Adam et al., 2021; McLean & Wilson, 2016). Accordingly, previous research has investigated the conditions required to satisfy SKs' expectations for personal, intuitive online service encounters with short waiting times at any time (Cheong et al., 2008; Scherer et al., 2015; Verhagen et al., 2014). An extensive research stream has addressed service encounters and the constellations of SKs, technology, and AI to deliver online services (Bitner & Wang, 2014; Keyser et al., 2019; Ostrom et al., 2019). A particular focus has been placed on the mechanisms that need to be implemented and the requirements that should be met to ensure high-quality service. This concerns, inter alia, the requirements for the behavior of SEs and AI (e.g., service scripts), the design of the appearance and interaction of technology and AI as a self-service interface (Sands et al., 2021). However, to fully leverage the AI's capabilities in service delivery, scholars have increasingly called for the adoption of a holistic perspective for its design and integration considering both technical and social systems (Alter, 2020; Bock et al., 2020; Lu et al., 2020). In this regard, Poser and Bittner (2021) and Poser, Wiethof, and Bittner (2022) contribute a suitable method to determine the application of AI to intangible service delivery by proposing consideration of the socio-technical interdependencies between SK, SE, and AI.

In this context, Poser, Wiethof, and Bittner (2022) consolidate understanding and further sense-making with the derivation and definition of basic design options for the integration of AI that is embedded into user interfaces or represented as a virtual agent into socio-technical online service delivery systems. Building on conceptual insights from the literature and analyses of online service interfaces as well as market solutions in practice, existing insights into AI-based solutions for text-based online service delivery were considered. As a result, in keeping with Nickerson et al. (2013) and Kundisch et al. (2022), a taxonomy that hierarchically structures options in terms of context, capabilities, output, integration, appearance, and underlying intelligence has emerged. In addition, the taxonomy presents the relationship of the options by defining a sequential ordering that assists in determining the division of tasks and activities as well as forms of interaction between AI and humans in service processes. Furthermore, the options expose the dependencies between AI and SEs in processes and tasks that have an impact on the interaction with SKs. These results provide a solid starting point for the extension and continuation of research that focuses on AI solutions that meet the socio-technical requirements of online service delivery work systems.

MD	Dimensions		Characteristics			
Service Context	D_1: Service Stages	NE	Frontstage	Backstage		
	D_2: Service Process Continuity	NE	Disconnected	Connected		
Capabilities	D_3: AI Role	NE	Support	Augmentation	Performance	
	D_4: Task Type	NE	Mechanical	Analytical	Intuitive	Empathetic
Deliverables	D_5: Knowledge and Data Insights	NE	Inquiry-related	Process-focused	Customer-related	Socio-emotional
	D_6: Performance Monitoring	NE	Human Agent Monitoring	AI Monitoring		
Integration	D_7: Hybrid Inquiry Handling	ME	Simultaneous	Consecutive - toward human	Consecutive - toward AI	Consecutive - alternating
	D_8: Level of AI Activity	NE	Reactive	Proactive		
	D_9: Form of AI Appearance	ME	AI-enabled agent	Embedded AI		
	D_{10}: AI Transparency to Customers	ME	Unknown	Known		
Intelligence	D_{11}: Data and Knowledge Processing	NE	Machine Learning	Rule-based Reasoning		
	D_{12}: Data and Knowledge Source	NE	Input before Interaction	Input during Interaction	Input after Interaction	

Note: MD = meta-dimension; ME = mutually exclusive; NE = non-exclusive

Figure 8. Taxonomy for AI integration (Poser, Wiethof, and Bittner, 2022)

A comprehensive analysis of the status quo in research and practice has revealed that the role of AI and the temporal alignment of service processes in hybrid request processing remains underdeveloped. Addressing this knowledge gap, Poser, Wiethof, and Bittner (2022) updated existing infusion archetypes for online service delivery (Keyser et al., 2019; Ostrom et al., 2019). Thus, constellations of entities SK, SE, and AI could be validated for the automation of service encounters in the frontstage. For the augmentation of encounters, two forms were introduced. Existing synchronous augmentation archetypes describe the synchronous support of service interactions that are visible or invisible to SKs. Asynchronous augmentation archetypes represent a new form of AI integration for online service encounters. Thereby, consecutive handling of requests is defined (see Figure 9, II & III).

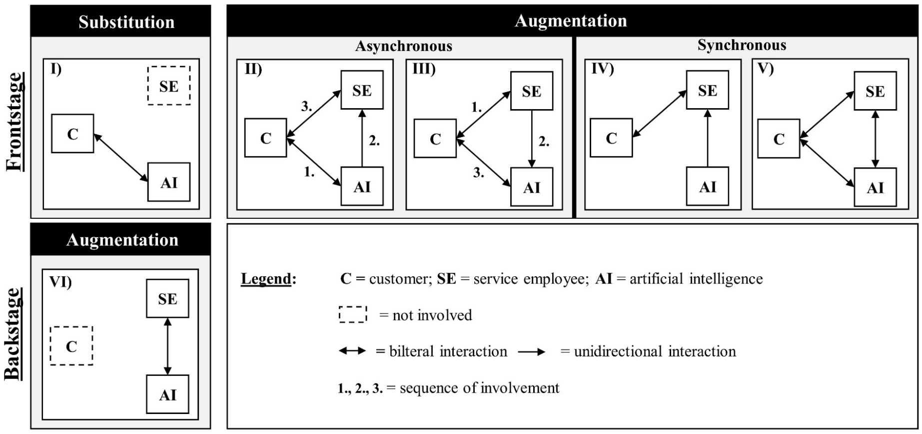

Figure 9. Updated AI infusion archetypes (Poser, Wiethof, and Bittner, 2022)

In connection with the service context (connected vs. disconnected service processes), two types of handovers have been introduced and defined for archetype II. A seamless handover refers to connected processes and allows for the immediate handover and effortless handling of a request by an SE (i.e., by taking over the same chat). Lag-time handover implies a time delay in request processing by the SE (i.e., a request sent as a ticket) due to disconnected processes (Poser et al., 2023; Poser, Wiethof, & Bittner, 2022). Thus, existing calls for hybrid service practices are answered with fallbacks to overcome the existing limitations in automated service interactions. In this respect, asynchronous augmentation with handover establishes and formalizes an approach for fallbacks in online service contexts to avert possible service failures in automated encounters or to initiate them owing to predefined requirements (e.g., sensible content).

Motivated to investigate the socio-technical relevance of online service at a task level, Poser and Bittner (2021) address the identification of integration points of AI embedded in user interfaces or represented as virtual agents in service processes. The results provide insights into the suitability of Richter et al.'s (2018) digital work design method, for a needs-based design of AI-infused service processes with knowledge-intensive activities. Thereby, the call for participatory processes in the alignment of AI and work practices is addressed (Makarius et al., 2020; Østerlund et al., 2021). By applying a bottom-up analysis to identify problems in service processes and activities, SEs were involved in determining the application of AI. In contrast to commonly applied top-down decision processes, the presented work analysis provides an approach to purposefully match AI solutions with the requirements of (sub-)tasks. With this approach, Poser and Bittner (2021) contribute six prevalent challenges in service processes and tasks in an online service delivery work system to the knowledge base. The conducted bottom-up analyses of internal IT support work systems revealed four challenges in the frontstage and two in the backstage (see Figure 10). Owing to these issues, SEs have to handle a high number of simple and recurring requests in direct contact with SKs, which overstrains the SEs' available time and mental capacities (Issue 1). In addition, the descriptions provided by SKs are inadequate and unstructured which hampers SEs' analysis of the content (Issue 2). During processing, the required information and knowledge for producing solutions cannot be found (Issue 3), and requests are escalated too early and to the wrong experts (Issue 4). Issues 5 and 6 relate to the challenges of SEs in the backstage regarding poorly documented requests and finding information and knowledge to process them. These validated challenges confirm and extend known issues and illustrate their impact in terms of slow service processes and the misinvested mental resources of SEs.

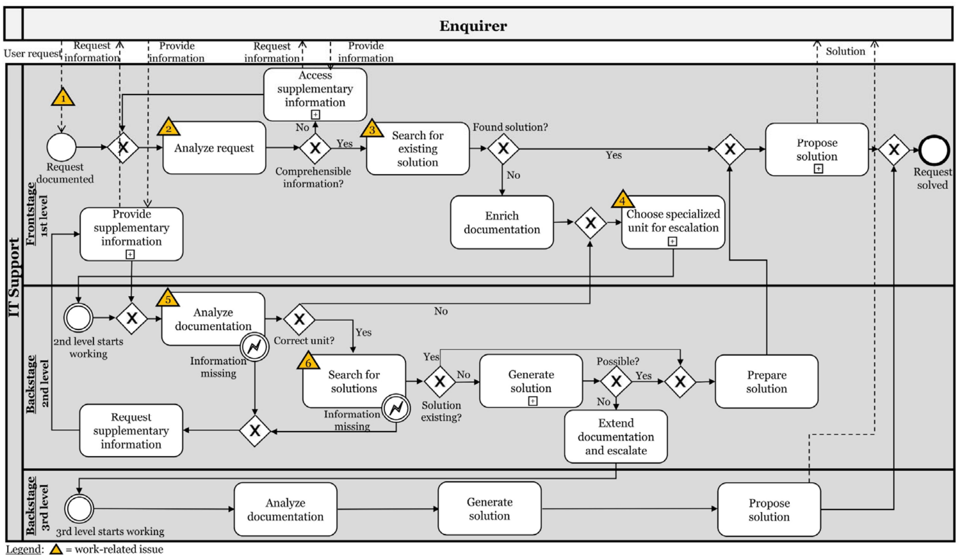

Figure 10. Challenges in online service processes (Poser & Bittner, 2021)

As a possible solution, Poser and Bittner (2021) provide a process redesign based on existing initial concepts and solutions in the literature for text-based AI-enabled virtual agents and embedded AI (see Figure 11). By purposefully integrating AI, activities in service delivery can be streamlined and SEs relieved from strain. To address Issues 1 and 2, standardizable service requests can be solved automatically or recorded in a structured manner, and handovers can be initiated during the initial contact with SKs. In addition, required knowledge for processing requests or escalating them to suitable experts can be proactively suggested to SEs (Issues 3,4, 5 and 6).

Overall, the contributions of Poser, Wiethof, and Bittner (2022), and Poser and Bittner (2021) add to an improved understanding of socio-technical interdependencies that have to be considered for the integration of AI-based solutions into online service delivery work systems. These results illustrate that the interrelationships have implications for process design and the allocation of tasks and activities. To achieve optimal service production and address existing problems, AI-based solutions should automate and augment tasks in online service work systems. In doing so, a hybrid form of online service delivery needs to be ensured to fully leverage the potential of AI.

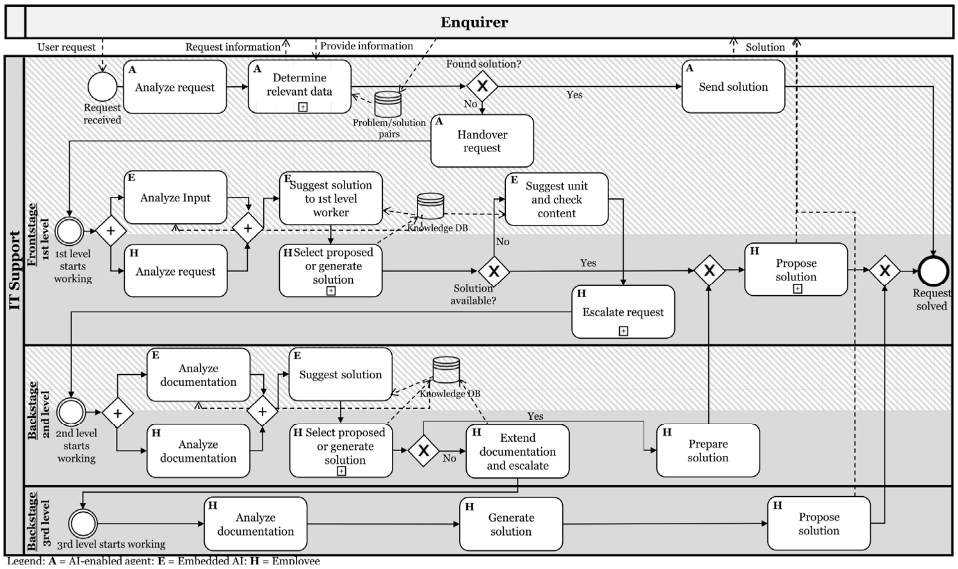

Figure 11. Online service process redesign (Poser & Bittner, 2021)

5.2 Hybrid Online Service Delivery

Building on the interplay of elements in the work system, the production of suitable AI-based solutions for hybrid online service encounters requires the design of interaction with AI. Therefore, the three influencing factors (user, system, and task) are considered in the design of AI-based solutions that are represented as virtual agents or embedded in user interfaces and employed by different users (SK and SE) for the automation and augmentation of online service encounters (see Figure 7). Depending on the approach, the design knowledge supports two types of hybrid online service encounters: consecutive and simultaneous. These forms of encounters enable the handover or support of interactions with SKs (see Figure 12).

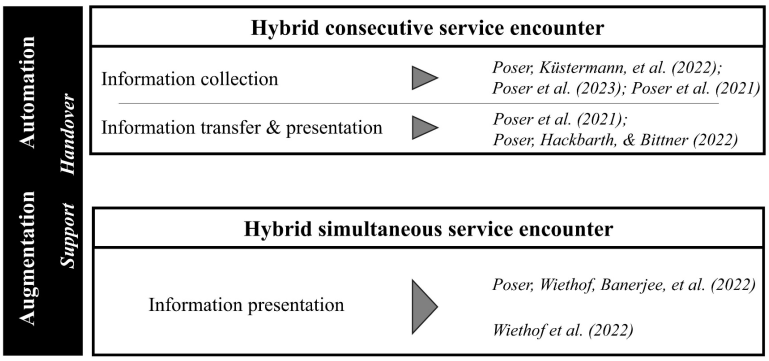

Figure 12. Overview of hybrid online service encounter forms

5.2.1 Hybrid Consecutive Online Service Encounters

The investigation of self-service technology as a service interface has a long tradition in service system and marketing science. One of the goals in previous work represents the improvement of communication with and the service experiences of SKs. In this context, the existing findings show that the integration of human elements and the creation of a service context enable social interactions. These factors can generate engagement through active participation in the co-creation of a service (Zomerdijk & Voss, 2010). In light of these insights, the humanlike capabilities of AI-based self-service solutions represented as virtual agents (i.e., CAs) have triggered the initiation of a number of research efforts focused on the intelligent automation of online service encounters (Zierau, Elshan, et al., 2020; Zierau, Wambsganss, et al., 2020). In these preceding studies, the design of anthropomorphic user interactions referring to communication style and visual representation has been conducted with domain-specific text-based CAs (e.g., Feine et al., 2019; Schuetzler et al., 2018). Although the distinct usability of humanlike service interaction with CAs is beneficial, the resulting expectations of SKs can be counterproductive as they can cause frustration due to the current limitations in terms of service delivery outcomes (Glushko, 2010; Luger & Sellen, 2016). To develop interventions in response to conversational breakdown or handle thematically sensitive issues (e.g., identity management) during service encounters, this dissertation extends the existing conversational repair strategies and adapts insights into service recovery strategies to AI-based online service encounters.

In this respect, Poser, Küstermann, et al. (2022) and Poser et al. (2023) provide design knowledge in the form of DPs that equip CAs with the ability to prepare the two handover types presented in this dissertation (seamless and lag-time handover). More specifically, a design for self-service interactions between SKs and CAs is provided. The design knowledge is distinct from that of previous findings as it is informed by requirements from SKs in terms of the interaction characteristics of CAs and from SEs in terms of documented input. The adoption of this socio-technical lens can ensure that the preceding activities of a CA support the subsequent task accomplishment of employees. To address the grand challenge of disconnected activities between CAs and employees, Poser, Küstermann, et al. (2022) establish four DPs that enable CAs to conduct pleasant conversations while supporting users in generating input through a structured process with four phases: (1) introduction, (2) generate, (3) build consensus, and (4) farewell. In the generate phase, a goal-oriented uptake of relevant information is achieved and follow-up questions from users answered (see Figure 13). More specifically, a design for self-service interactions between SKs and CAs is provided. Informed by the concept of facilitation from collaboration research, the humanlike execution of facilitative acts by a CA supports users in generating elaborate and homogenous input that meets the requirements of employees for further processing. The intuitive and conversational interaction ensures a high level of engagement and thus increases the likelihood that users are (will remain) motivated to provide input.

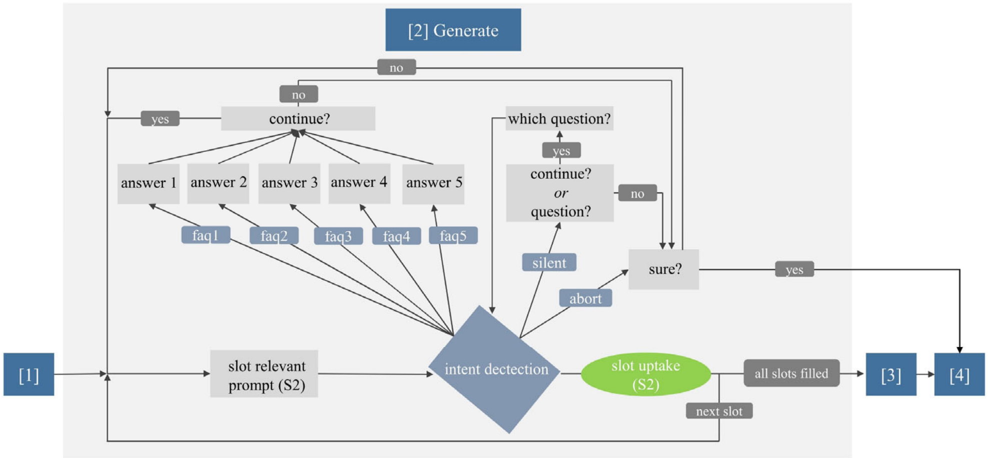

Figure 13. Facilitation process for user engagement during input generation (Poser, Küstermann, et al., 2022)

As an advancement, Poser et al. (2023) build on this design knowledge with its high projectability, medium abstractness, and high concept density and apply it to an online service delivery environment (internal IT support). Through a practice-oriented determination of design requirements, the adaptation and fitness of the existing DPs were achieved. In particular, the determination of a category by the CA to pose relevant questions, the indication of mandatory input, and the provision of process step-based help were identified as domain-specific requirements. As a result, four adapted DPs emerged to define the behavior of CAs in self-service interactions prior to handovers (see Figure 14).

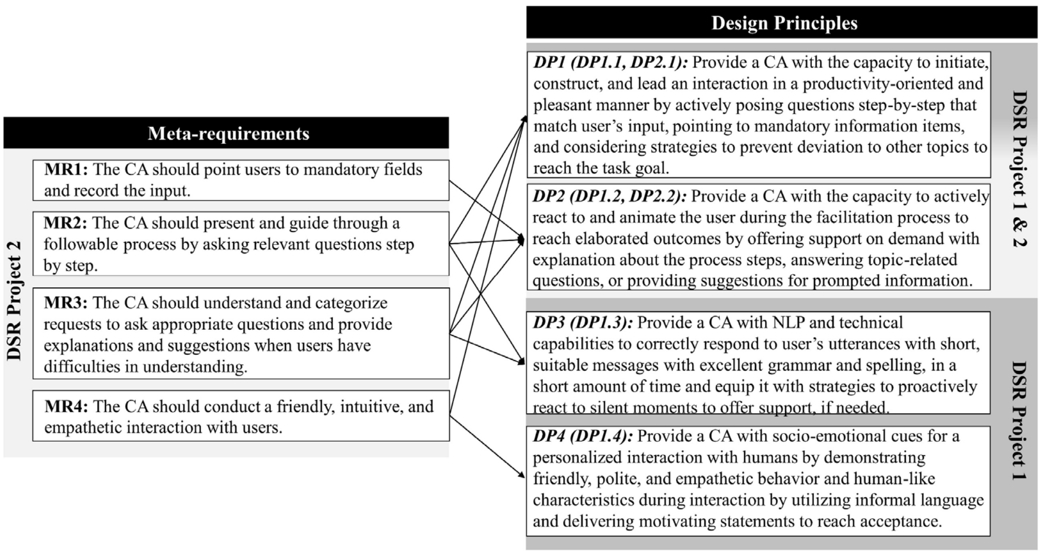

Figure 14. DPs for the elicitation of information (Poser et al., 2023)

The implementation of these DPs has proven to be beneficial for SKs and SEs. For SKs, the effectiveness of submitting a request increases as they receive step-by-step support with explanations, suggestions, or examples. This approach leads to the improved completeness, specificity, and comprehensibility of the content, which increases the efficiency of SEs in subsequent processing. Poser et al. (2023) have thereby produced a novel approach to designing self-service interactions for the online delivery service contexts by combining theoretical insights from human facilitation processes and the service script concept (see Figure 15). This promises to elicit a supportive goal-directed documentation of information via CAs to prepare hybrid service recovery with direct (seamless handover) or delayed (lag-time handover) processing by SEs.

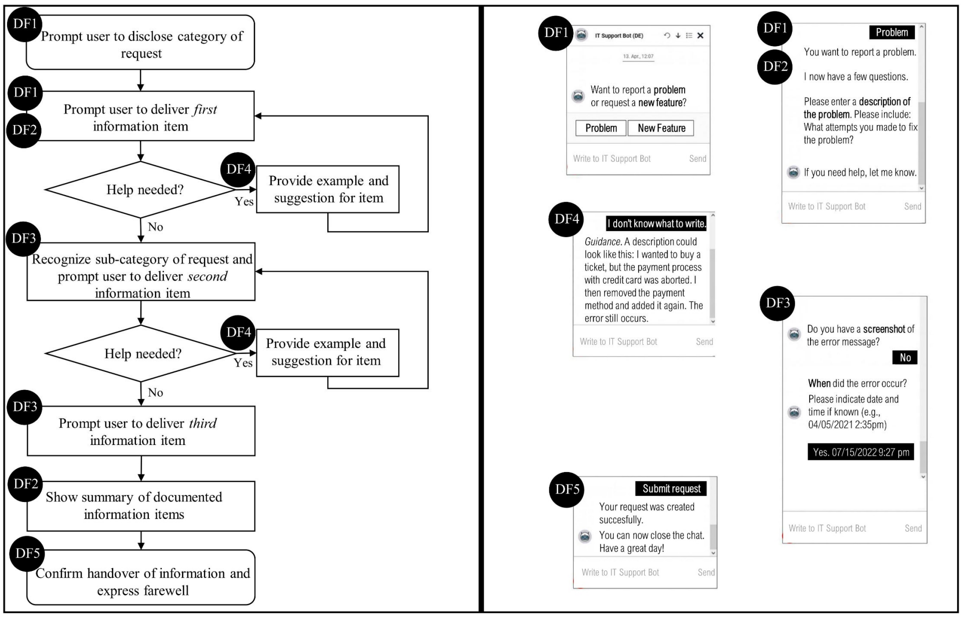

Figure 15. Service script for facilitating the information elicitation process (Poser et al., 2023)

Poser et al. (2021) derive additional design knowledge for seamless handover that refers to information collection, transfer, and procedural integration. Guided by the distinct requirements of real-time handovers, which should be associated with low waiting times for SKs and support SEs in continuing processing, abstract DPs have been developed. These define the capabilities of CAs for handling handover situations, with a focus on the initiation of the handover including the transfer of relevant information for SEs to continue processing (see Figure 16).

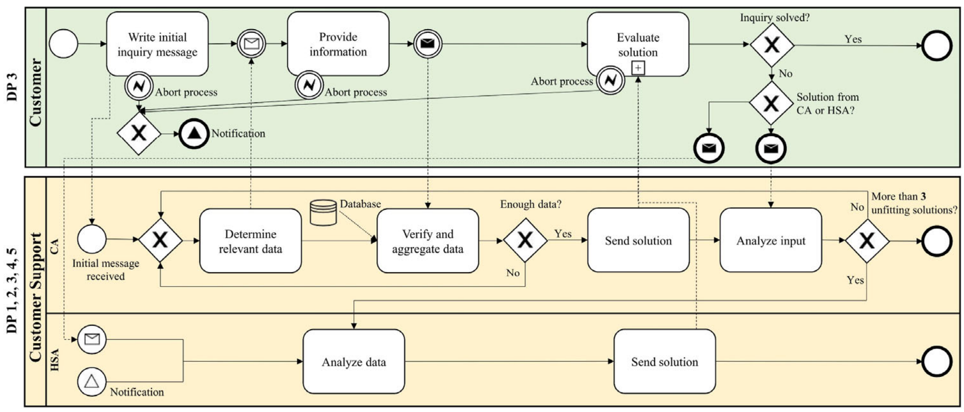

Figure 16. Process for seamless handovers from CA to SE (Poser et al., 2021)

As a continuation of the design for a seamless handover, Poser, Hackbarth, and Bittner (2022) identify DPs for the construction of a handover user interface for SEs (see Figure 17). This design knowledge considers, for the first time, the recovery of failed CA-performed online service delivery, considering the socio-technical interaction between SK, SE, and CA. To realize a successful service experience and mitigate the negative impact of an impending service failure, a seamless handover places high demands on SEs. With the goal of avoiding waiting time and the repetition of questions for SKs, human-centered design knowledge considers the human capabilities of information processing and the production of mental problem representations.

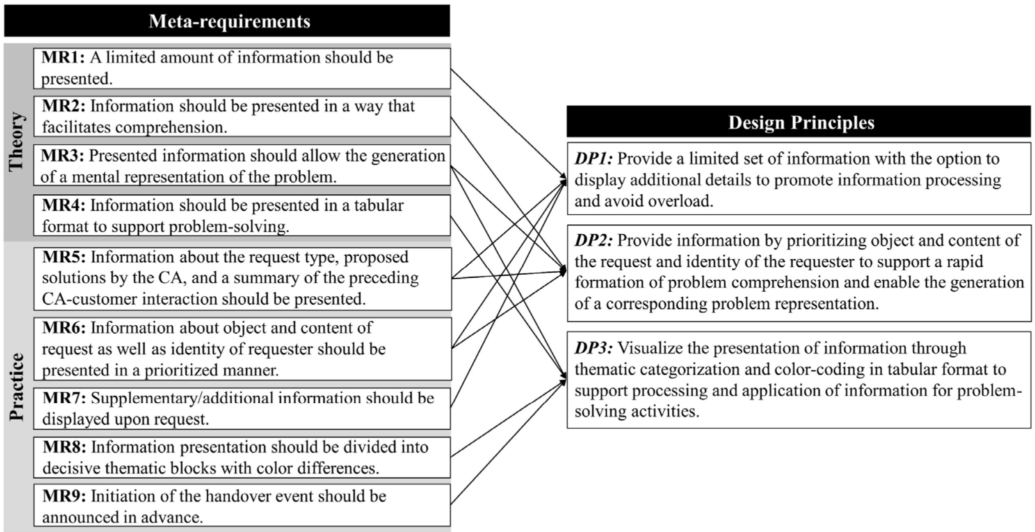

Figure 17. DPs for the design of a handover user interface (Poser, Hackbarth, and Bittner, 2022)

The initially reduced display of particularly relevant information items, as well as the thematic arrangement and presentation of the content, enables a goal-directed continuation, as overload is avoided and the formation of a mental problem representation is promoted (see Figure 18). By determining the appropriate information types, SEs have the opportunity to apply individual strategies on how to continue the interaction. Poser, Hackbarth, and Bittner (2022) provide DPs that are useful for text-based online service delivery, as this improves SEs' response time and promotes SK-centric interactions through reduced time pressure.

Overall, design knowledge in the form of DPs and design entities for AI-based solutions that enable hybrid consecutive online service encounters contributes to the body of knowledge on the form of actionable knowledge for the orchestration of text-based hybrid online service activities. The increase in robustness to complete service failure is achieved with two handover types (seamless and lag-time handover) by integrating touch points and ensuring their fitness for necessary information exchange.

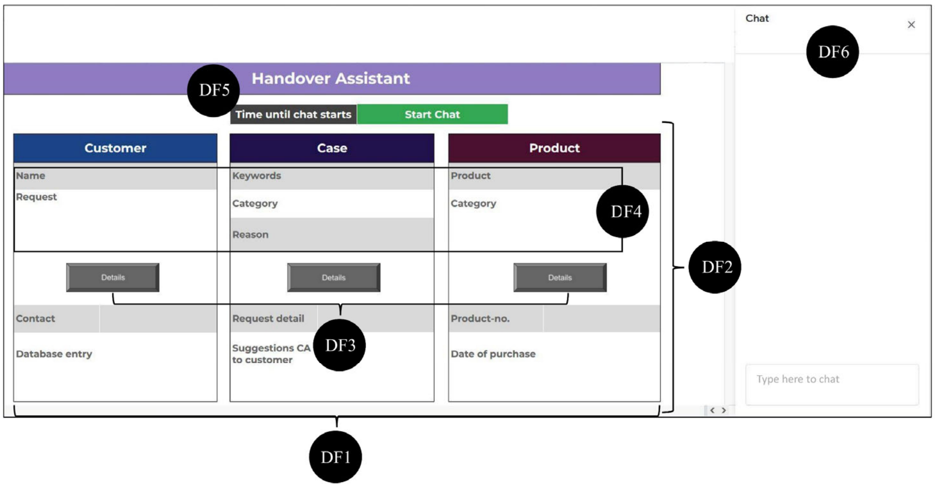

Figure 18. Handover user interface prototype (Poser, Hackbarth, and Bittner, 2022)

5.2.2 Hybrid Simultaneous Online Service Encounters

To extend the leverage of AI, the importance of combining the capabilities of humans and AI is increasingly postulated (Wilson & Daugherty, 2018). Augmentation approaches are pursued in different domains to employ AI for the elevation of human decision-making and problem-solving behavior (e.g., management decisions) (Ebel et al., 2021). In the context of online service delivery, however, knowledge of how to establish coworking between AI and SEs is scarce (Keyser et al., 2019; Robinson et al., 2020). More specifically, there is a lack of approaches that address the design of user-AI interaction in relation to the requirements of the contextual conditions of online service delivery.

Aiming to support SEs in text-based online service encounters while simultaneously exploiting the benefits of augmentation for gradual AI advancements, Poser, Wiethof, Banerjee, et al. (2022) and Wiethof et al. (2022) contribute design knowledge for HISs. In contrast to previous work that addressed general design guidelines for or technical aspects of HISs, the focus is on human-centered interaction design knowledge in the form of DPs. The capabilities of AI to rapidly analyze and propose suggestions in sync with the encounters can thereby be used to provide support to SEs. With a specific focus on collaboration between embedded AI and humans to create the best possible conditions for online service encounters, the derivation in Poser, Wiethof, Banerjee, et al. (2022) is guided by three basic human needs for optimal performance. Based on meta-theoretical insights into the self-determination theory concerning human motivation, the need for autonomy and competence to achieve desired goals, and the establishment of relatedness are addressed. The prescriptive statements build on kernel theories about human cognitive processes that are related to decision-making, information processing, the evaluation of advice, and the perception of AI (see Figure 19).

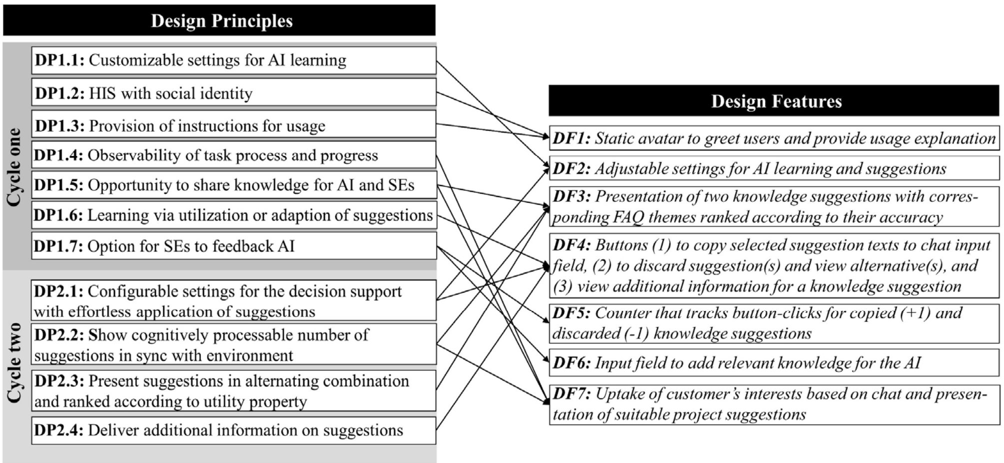

Figure 19. DPs for HISs with embedded AI (Poser, Wiethof, Banerjee, et al., 2022)

Building on Wiethof and Bittner (2022), Poser, Wiethof, Banerjee, et al. (2022) show that the human-centered design of an HIS with AI embedded in a user interface supports SEs in decision-making during the online encounter while ensuring task mastery via a feeling of autonomy. The complexity of the task is thereby reduced in several ways. Monitoring the dynamic interaction with SKs can be enhanced by providing a basis for decisions on how to continue the conversation (see Figure 20, DF7) and suggestions for the execution of problem-solving activities (see Figure 20, DF3). The presentation and format of the suggestions presented by the AI therefore increase efficiency, generate relief, and result in time savings for SEs.

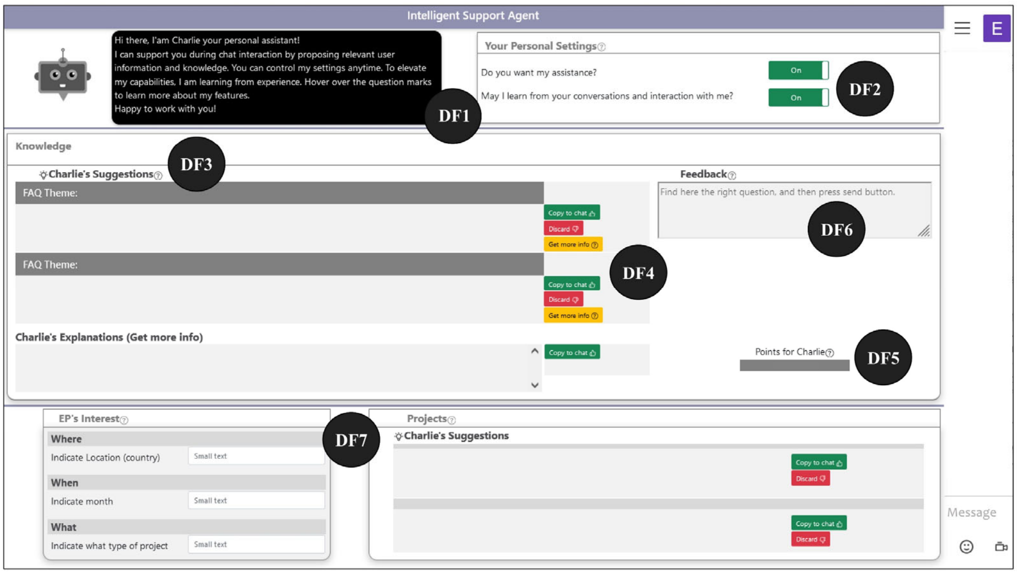

Figure 20. HIS prototype with embedded AI (Poser, Wiethof, Banerjee, et al., 2022)

Similarly, Wiethof et al. (2022) investigate the augmentation of text-based online service encounters with an HIS that comprises AI represented as a virtual agent. Focused on creating a symbiosis between AI and SE, the produced design knowledge facilitates humanlike collaboration during online service encounters. Previous research has shown that CAs generate expectations of human behavior in joint task processing based on their social cues (Poser & Bittner, 2020). To promote this relatedness, Wiethof et al. (2022) use the input-process-output model from team research to determine the capabilities (input), activities to achieve the common goal (processes), and fulfillment of SEs' and SKs' needs (output). Based on the characteristics of AI that Poser, Wiethof, and Bittner (2022) identify for online service delivery, five DPs are defined (see Figure 21). In the role of an artificial teammate, CAs achieve high usefulness and support SEs in responding quickly to a changing conversation. In addition, personalization of the interaction with SKs is promoted by offering different suggestions based on the sentiments of SKs.

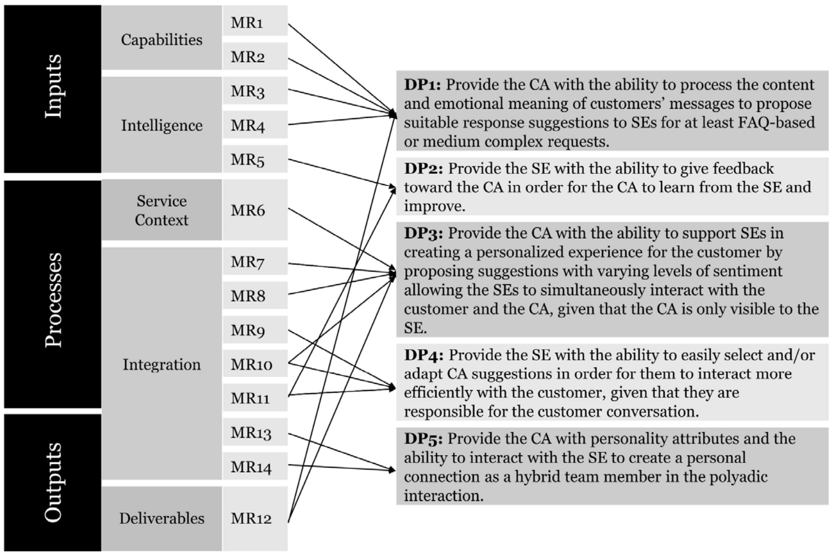

Figure 21. DPs for HISs with AI represented as a virtual agent (Wiethof et al., 2022)

Overall, the results of Poser, Wiethof, Banerjee, et al. (2022), and Wiethof et al. (2022) contribute to establishing augmentation scenarios in online service delivery work systems. By considering human needs and mental and cognitive processes, a purposeful integration of the complementary capabilities of AI and SE can be achieved. As a result, an increase in effectiveness in online service encounters can be realized by elevating the experience for SKs and managing the limited resources of SEs.

5.3 Overall Theoretical Contribution

By addressing the RG of this thesis, validated knowledge has emerged for the human-centered design and integration of AI-based solutions that are represented as virtual agents or embedded in user interfaces to enable hybrid online service production. The results adapt and complement existing knowledge of CAs and HISs and advance the evolution of the two knowledge bases. By capturing and describing the problem space, insights into the environmental context have been generated in the form of existing operational challenges for the delivery of online service. In addition, the performed design activities contribute to an improved understanding of the role of AI-based solutions and their integration into online service delivery work systems with revised infusion archetypes. In addition to these contributions to the Ω-knowledge base about real-world phenomena, the core results of this dissertation in the form of actionable design knowledge and design entities contribute to the λ-knowledge base. In keeping with Gregor (2006), this λ-knowledge resembles theoretical design knowledge with a prescriptive nature. Represented by a model, abstract DPs, and situated instantiations, this novel prescriptive knowledge represents a nascent design theory for design and action (type 5) to establish hybrid online service delivery for intangible services by constructing suitable AI-based solutions (Baskerville et al., 2018; Gregor, 2006; Gregor & Hevner, 2013). According to Gregor and Hevner (2013), the achieved contributions of the type "improvement" span abstraction levels 1 and 2 by providing evaluated instantiations and generalized DPs for known problems.

The presented solution design knowledge in this dissertation addresses the limitations and the untapped potential of existing automation and augmentation approaches for text-based online service encounters and generates missing insights into the relevant socio-technical interrelationships between SK, SE, and AI. Addressing a class of problems in related application domains in the context of online service delivery, this prescriptive knowledge has an idiographic character, as it provides solution knowledge to tackle specific challenges (Drechsler & Hevner, 2018). This characteristic could be confirmed with the performed research activities, which demonstrate the utility and fulfillment of goodness criteria in the application contexts of customer service and internal IT support. At the same time, the solution design knowledge specifies meta-artifacts with a nomothetic character that can be used as theoretical knowledge for projections (Baskerville & Pries-Heje, 2019; vom Brocke et al., 2020). To propagate and provide an abstraction of the accumulated design knowledge, the concept of design patterns is used. Accounting for the relevance of problem-solution relationships in DSR, four patterns present heuristic propositions that can be used, extended, or transformed for the same or similar recurring challenges (Petter et al., 2010; van Aken, 2004; vom Brocke et al., 2020) (see Table 14).

In combination with the renewed infusion archetypes and prescriptive description of decision options for the integration of AI that are presented in this dissertation, the patterns inform the implementation of hybrid text-based encounters in the context of automation and/or augmentation approaches in online service delivery work systems. More specifically, along a continuum, the patterns provide prescriptive solution knowledge for designing AI-based solutions represented as virtual agent or embedded in a user interface. Patterns 1 and 2 provide design knowledge for the automation of online service encounters. The resulting hybrid consecutive online encounters ensure that the preceding activities of AI (e.g., CAs) in interactions that are adapted to the needs of users are executed in such a way that employees are supported in effectively continuing the processing of a request after the handover. The problem-solution proposition of pattern 3 can be used to design the interconnection between the activities of AI and employees in hybrid consecutive encounters for continued processing after handover by considering the cognitive restrictions of humans.

Table 14. Design patterns for hybrid online service delivery

	No.	Design patterns		
		Challenge	**Solution**	
			Representation	*Properties*
Automation	**1**	Limitations and/or chosen restrictions on the automated processing of requests with unconnected activities of AI and employees provoke destructive and inefficient outcomes.	AI-enabled agent	Equip agentic AI with the capacity to monitor the interaction and progress of request processing to enable the initialization of handovers to employees to avert service failure while adhering to predefined criteria.
	2	Unsystematic and unstructured capturing of input impedes the generation of suitable solutions for requests by AI and/or employees.	AI-enabled agent	Equip agentic AI with the ability to lead through a goal-focused, step-by-step process in accordance with an identified category to assist users with supplying information in a pleasant, engaging, and humanlike manner to provide a foundation for decision-making and/or action implementation after handover.
	3	High time pressure and unavailable information hamper the comprehension of request-related content and causes high demands on cognitive processes.	AI-enabled agent/ embedded AI	Equip agentic AI with the capability to present a limited volume of relevant information with visual support and effortless utilization to avoid cognitive overload and promote the formation of a mental representation of the request.
Augmentation	**4**	Dynamic and continuous changes in the environment (synchronous interaction) cause overstraining and complex decision-making situations involving analytical and empathic components.	AI-enabled agent/ embedded AI	Equip agentic AI with the capacity to proactively present suggestions in sync with the environment by sorting them based on utility properties along with the option for additional explanatory information to serve as a basis for decisions on the course of interaction, provision of information, or performance of problem-solving acts while ensuring control over and relatedness with the agentic AI.

In addition, along with pattern 3, pattern 4 serves as prescriptive design knowledge for the augmentation of online service delivery with hybrid simultaneous encounters. The solution design knowledge defines human-centered properties of AI represented as a virtual agent or embedded in user interfaces to support employees in dynamic interactions to make decisions about performing relevant activities.

Overall, the result of this thesis offers theoretical contributions for the application purpose of AI, future work scenarios in online service delivery work systems, delegation principles for agentic AI, and human-AI interaction.

Regarding the purpose of application, research has mainly been characterized by contradictions regarding the use of AI in companies (Brynjolfsson & McAfee, 2014). Raisch and Krakowksi (2021) describe tasks and activities as either automated or augmented. Therefore, the paradoxical tension between these approaches has not been considered in research and practice. However, the overemphasis on one approach for a set of (sub-)tasks and activities can lead to adverse effects for organizations, as the benefits of advancing AI's capabilities are not realized (Benbya et al., 2021; Raisch & Krakowski, 2021). IS research also highlights "an emerging tension between the automation and augmentation of human work" that should be managed using suitable approaches (Benbya et al., 2021, p. 285). By achieving synergy between the approaches with suitable AI applications, the benefits of automation and augmentation can be enabled via the redesign and adaptation of work processes. Against this background, the developed solution design knowledge in this thesis allows this synergy in online service delivery work systems. A purposeful substitution of standardizable activities that were previously performed by humans can thereby be achieved while ensuring a reduction in service failures with handovers. Moreover, by augmenting activities through collaboration between AI and employees, the evolution of AI's capabilities can be ensured via human-in-the-loop procedures. The realization of this synergy regarding the online service delivery of knowledge-intensive intangible services can provide the basis for other related research areas that deal with a redistribution of information- or knowledge-intensive tasks.

The creation of synergy between the approaches of automation and augmentation has implications for the design of knowledge-intensive (service) work. The results of the thesis show that the automation and augmentation of (sub-)tasks are associated with impacts on existing work practices. To realize the benefits, a redesign of processes and the establishment of a novel allocation of activities to AI and employees for (sub-)tasks are required to accommodate the arising socio-technical interdependencies. In this context, the dissertation shows that the adoption of a socio-technical lens, according to Alter (2013), is useful. The social and technical components are thereby defined as one work system that supports a holistic perspective on managing the interplay of people, technology, and information. Moreover, the active involvement of employees helps to identify the optimization potential in their work and purposefully combine the capabilities of AI and humans. Furthermore, an improvement in activities can be achieved by reducing misinvested resources (e.g., time and mental capacities) by solving existing challenges of employees The dissertation thereby answers the call for employee involvement in determining the integration points and characteristics of AI (Lu et al., 2020; Makarius et al., 2020; Østerlund et al., 2021). Therefore, the results indicate that a socio-technical work analysis from the perspective of employees is recommended. In combination with a standardized illustration of existing and future work practices, challenges can be identified and addressed. Furthermore, the results of the dissertation suggest that AI-based self-service and human service should be connected via hybrid service processes to improve robustness to failure and the handling of critical requests in automated service encounters.

The production of the hybrid work practices and processes addressed in this dissertation also has implications for research on delegation principles for agentic IS and AI. The increasing capabilities of AI to substitute or support (sub-)tasks require delegation principles that should be adapted to the task-related prerequisites and characteristics of AI and humans (Baird & Maruping, 2021). In the context of this research, this dissertation provides insights into the dyadic delegation between AI and employees regarding online service delivery. The results show that SEs should be responsible for the outcome of online service encounters in hybrid service delivery settings. To meaningfully complement AI and SEs, delegation in automated and augmented service encounters can be realized according to the four information-processing activities in knowledge-intensive tasks: (1) information acquisition, (2) information analysis, (3) decision selection, and (4) action implementation (R. Parasuraman et al., 2000). When implementing automation and augmentation approaches, delegation occurs at breakpoints where AI either hands over an interaction (hybrid consecutive encounter) or provides support during the interaction (hybrid simultaneous encounter). With respect to the four information-processing activities, the thesis indicates that delegation from AI to SE should take place after AI executes the first two activities. Information and decision support can thereby be provided, which can promote the effectiveness of the SE's subsequent behavior.

In terms of the design knowledge for the creation of AI-based solutions, the results of the dissertation indicate that the characteristics and representation of AI as virtual agents or embedded in user interfaces should be determined according to deployment and integration goals. For the realization of hybrid simultaneous online service encounters, validated design knowledge helps achieve task-specific support for SEs with embedded AI and virtual agent solutions. By considering theoretical insights into humans' mental and cognitive processes, the effectiveness of SEs' behavior can be elevated. Thus, the results reveal that by accounting for human processes in terms of information processing, decision-making behavior, and problem-solving behavior, the dynamics, complexity, and richness of information in text-based, synchronous online service encounters can be matched. Furthermore, insights from this dissertation show that the design of the interaction with users in automated encounters should include elements that prepare required handovers to employees. By incorporating structure-giving interaction processes in hybrid consecutive online service encounters, the subsequent processing by employees after handover can be improved, which can reduce waiting times for SKs until requests are resolved.

6 Practical Contributions

In keeping with the problem-solving DSR paradigm, the research endeavor of this dissertation is motivated by existing and prevalent challenges in the environment. Hence, in addition to the theoretical contributions to the knowledge bases, the outcome also provides design knowledge with a utility character for application in practice to address the identified problems (Hevner & Chatterjee, 2010; Hevner et al., 2004; Venable, 2006). Guided by goodness criteria from practice, the generated solution design knowledge and its instantiations were tested for applicability, effectiveness, and efficiency in evaluation procedures with appropriate stakeholders to obtain results concerning proof of applicability and usefulness (Pries-Heje et al., 2008; Sonnenberg & vom Brocke, 2012). With respect to the problem space that spans the application domains of customer service and internal IT support, the resulting implications for practice are suitable for online service delivery work systems with text-based service interfaces.

Overall, the outcome of this dissertation has several implications for practice. The increasing shift in SKs' preference toward chat-based service encounters has led to the widespread implementation of text-based AI in organizations to generate value via increased efficiency and effectiveness in online service delivery. Facing pressure to ensure a competitive edge, organizations across industries are following the trend of using AI-based solutions to leverage their benefits in terms of the short waiting times for solution generation, high accessibility, intuition, and personalization of online service offerings. To reduce the existing limitations of applying an automation approach and promote the benefits of implementing an augmentation approach for text-based online service encounters, the practical contributions of this dissertation refer to the integration and design of suitable AI-based solutions represented as virtual agents or embedded in user interfaces in work systems while ensuring hybrid online service delivery.

6.1 Integration of AI for Hybrid Online Service Delivery

Regarding the integration of AI-based solutions for the delivery of hybrid online services, the dissertation addresses two relevant topics for practice.

First, the dissertation deals with the analysis of existing service processes and activities that can help practitioners identify challenges and leverage potential for improvements through AI. More specifically, in keeping with the existing theoretical findings, the thesis presents a socio-technical approach to work analyses in online service delivery work systems. To ensure a holistic result, practitioners should conduct analyses that cover both the social and technical components of the work system. Practitioners can thereby reveal and consider interdependencies between processes and activities that are or should be performed by AI and SEs using information to co-create service with SKs. Another pertinent finding in this context is the usefulness of involving relevant employees and stakeholders in the data collection phase. In doing so, practitioners can integrate and use important contextual knowledge to conduct goal-directed analyses of their work systems. Apart from these insights into conducting analyses, the dissertation identifies existing challenges and provides a redesign of service processes by integrating AI-based solutions using the example of internal IT support. These findings on the representative as-is situation can help practitioners conduct a focused analysis of their own existing service processes and activities. With the provided procedural illustration of the as-is situation, they can examine whether the same or similar problem dimensions that adversely affect service production exist in their work systems. Furthermore, the presented to-be solution in the form of a process model can serve organizations as a template to conveniently streamline their service processes and activities by integrating one or several of the proposed AI-based solutions. The validity of the generated service processes (as-is situation and to-be solution) could be demonstrated in a qualitative evaluation procedure with domain experts (Poser & Bittner, 2021). Hence, the use of the approach is recommended to holistically capture and redefine service processes in the context of internal IT support.

In addition, the results of the dissertation can help practitioners make informed decisions about implementing AI-based solutions as part of their automation and/or augmentation approaches. In this context, the presented essential options for the integration of AI-based solutions into an online service delivery work system can be used. As a basis for deciding on the integration dimensions, decision-makers can apply the renewed infusion archetypes in combination with Poser, Wiethof, and Bittner's (2022) taxonomy to elevate the production of text-based online services. By using the visualized archetypes and considering the design options in the taxonomy, the basic purpose of the application can be determined. This allows decision-makers to define the essential characteristics of AI-based solutions that are relevant to realizing the automation and/or augmentation of text-based online service delivery. Validity and usability could be demonstrated by evaluating the taxonomy with experts from research and practice. In addition, the application has produced reliable results (Poser, Wiethof, & Bittner, 2022). Consequently, the taxonomy can provide assistance to practitioners in two ways. First, the taxonomy presents users with a concise visual overview of all decision options and their interdependencies. Second, the hierarchical sequential order of meta-dimensions, dimensions, and characteristics in the taxonomy allows practitioners to systematize their decision-making process. Besides planning the implementation of AI integration, the taxonomy can help practitioners analyze existing AI-based solutions as part of online service delivery work systems. Therefore, the sequence of design options can also help to analyze the potential for improvement of an existing AI-based solution and its socio-technical embeddedness in the work system.

In addition to insights into how to conduct work analysis and decision-making processes for AI integration, this dissertation presents state-of-the-art AI solutions that can be deployed for text-based online service delivery. On the one hand, the presented solutions refer to AI applications from the scientific literature (Poser & Bittner, 2021; Poser, Wiethof, & Bittner, 2022). On the other hand, market solutions and the implemented AI applications of a selection of global companies are presented (Poser, Wiethof, & Bittner, 2022). With this overview, companies can inform themselves about the solutions that can currently be implemented.

6.2 Design Knowledge for Hybrid Text-based Online Service Delivery

The prescriptive knowledge produced in this dissertation takes two forms. On the one hand, the four design patterns represent an aggregated form of accumulated design knowledge. Thus, the design patterns can serve practitioners as a basic orientation and build an understanding of problem-solution relationships in the context of online service delivery. On the other hand, detailed human-centered prescriptive solution design knowledge is presented in the form of design requirements and DPs. This knowledge and its instantiation can help practitioners in the production and design of AI-based solutions that are represented as virtual agents or embedded in user interfaces to realize hybrid, text-based online service encounters as part of automation and/or augmentation strategies.

In the context of automation projects, practitioners can use the results of this dissertation to design CAs and a user interface for the delivery of hybrid text-based online service. To prevent possible service failure owing to conversational breakdown or to enable responses to sensitive requests, the DPs can assist in designing a CA for interaction with SKs. By combining the facilitation concept with service scripts, CAs can be equipped with the ability to monitor self-service encounters, collect necessary information, and initiate handovers to SEs (Poser et al., 2023; Poser et al., 2021). In an interview-based evaluation with domain experts, the basic skills of CAs in regard to initiating handovers were found to be relevant (Poser et al., 2021). Furthermore, the quantitative evaluation of interactions with a CA that facilitated conversations has revealed SKs' satisfaction with the interaction. In addition, information gathering for handovers has been shown to be effective because of its high comprehensibility, completeness, and specificity (Poser et al., 2023). As a result, actionable design knowledge is suitable for organizations to implement two forms of handovers that can prevent SKs' dissatisfaction with self-service technology. On the one hand, lag-time handovers can be implemented when the information documented by the CA is relayed to SEs via tickets and processed with a certain time delay. On the other hand, seamless handovers can be implemented. In this case, the conversation is transferred live from the CA to an SE, who creates a solution for the request. This dissertation provides knowledge for designing a user interface to ensure seamless continuation after a live handover. The results of a mixed-method evaluation demonstrate the effectiveness of the instantiated design knowledge. With the user interface, SEs were able to quickly develop an understanding of the problem, find appropriate information, and continue the conversation despite time pressure and without cognitive overload (Poser, Hackbarth, & Bittner, 2022). Accordingly, this human-centered design knowledge can be applied in organizational settings to enable SEs to effectively continue the conversation. In addition to the form of presentation, the identified information items can help practitioners make context-specific adjustments to their user interfaces.

Apart from the insights into the implementation of the automation approach, the dissertation presents human-centered design knowledge for the augmentation of text-based online service encounters. This knowledge refers to the interaction design of AI-enabled virtual agents or embedded AI as part of HISs. The design knowledge presented in this dissertation can help practitioners achieve optimal integration of the capabilities of AI and SEs while considering the context-specific conditions of synchronous chat-based service interactions. Accounting for human capabilities related to information processing and decision-making in dynamic situations, the presented DPs can help practitioners create a human-centered design of an HIS with embedded AI. At the same time, this type of HIS allows companies to benefit from the included human-in-the-loop process by systematically developing AI capabilities. Accordingly, the design knowledge, validated through a mixed-method evaluation, can be used in organizations to achieve cognitive relief, time savings, and improved efficiency of SEs in synchronous customer interactions (Poser, Wiethof, Banerjee, et al., 2022). Furthermore, the considered basic human needs (autonomy, competence, and relatedness) to ensure task mastery provide guidance for practitioners in the implementation of human-centric AI solutions. Besides an HIS with embedded AI, this dissertation presents solution knowledge for the design of an HIS with an AI-enabled virtual agent. These DPs can assist practitioners in realizing augmentation through a humanlike collaboration between AI and SE. As CAs can be equipped with a set of social cues, the intuition of SEs' support and interaction with AI can be positively influenced.

Overall, solution design knowledge can be used in practice to realize hybrid service delivery to leverage untapped potentials by improving the automation and augmentation of online service delivery with suitable AI-based solutions. On the one hand, the current drawback of automated service delivery in the form of service failures can be reduced with hybrid consecutive online service encounters. On the other hand, the time and mental resources of SEs can be effectively managed as part of augmented service delivery with hybrid simultaneous online service encounters that involve a human-centric collaboration between AI and SEs. In addition, practitioners can use the design knowledge to create a synergy between the approaches by combining the automation and augmentation of online service encounters. By implementing, both, hybrid consecutive and simultaneous online service encounters, service providers can promote the handling of service encounters with varying degrees of knowledge depth – ranging from simple information-based to complex advice-based content – and the required empathy. Furthermore, by simultaneously automating and augmenting online service encounters, the capabilities of AI for autonomously handling SK requests can be developed successively via the interaction between AI and SEs as part of HISs. The value creation for companies can thereby develop positively over time by increasing the efficiency of online service delivery through the use of AI.

7 Limitations

This dissertation has a few limitations that have an impact on the relevance, rigor, and projectability of the outcome. The limitations relate to the definition of the problem space, the production of the solution space, and their connection via evaluation procedures.

The problem space addresses the problems and challenges in the environment (Hevner & Chatterjee, 2010). In this cumulative dissertation, a broader class of problems is addressed as two related application domains were considered. To derive the motivation, the challenges and status quo were captured by analyzing selected organizations and use cases. The resulting findings were influenced by this selection, as an expansion of the studied companies or the restriction to one application context could have yielded a different problem statement. To counteract this issue, purposeful sampling (Poser & Bittner, 2021) and stratified random sampling (Poser, Wiethof, & Bittner, 2022) were chosen as strategies to ensure that the selection of companies, stakeholder, and employees was representative. As part of the research activities for the definition of the problem space, qualitative methods for data collection and analysis were used. The design requirements and goodness criteria were thereby determined. To capture the subjective reality of experts in the environment, semi-structured interviews were conducted. The analysis of interview transcripts can be influenced by the subjective interpretations of researchers, which may distort the meaning of the reported reality (Myers & Newman, 2007). To address this risk, established methodological procedures for conducting expert interviews and qualitative content analyses with established coding approaches were applied. In addition, multiple researchers were involved in the data analysis and coding procedures to achieve higher objectivity.

To determine suitable design knowledge as part of the solution space, the extant literature from knowledge bases was considered. By including existing design knowledge and entities, this dissertation has aimed to achieve contributions by building on them in the research process. In doing so, the selection of databases, the determination of search terms, and decisions about the inclusion of existing publications can influence the generation of solution design knowledge due to the neglect of relevant insights. To limit this effect, established methods have been used to promote validity, reliability, and objectivity in the selection of existing knowledge (vom Brocke et al., 2015; vom Brocke et al., 2009; Webster & Watson, 2002). In the production of the solution space, design knowledge is generated based on environmental requirements and existing scientific knowledge (Gregor, 2009; Hevner, 2007). The formulation of design requirements and DPs and the transparency of the development process can influence reusability. To ensure a uniform description, DPs were written according to their categories using an established template (Gregor et al., 2020). In addition, the relationships between design requirements and DPs were comprehensibly illustrated with mapping diagrams and described in detail.

A further limitation relates to the evaluation of the produced design knowledge with or without its instantiation via prototypes. To establish the link between the problem and solution spaces, the utility, effectiveness, and efficiency of the produced design knowledge should be demonstrated through evaluation steps (Venable, 2006; vom Brocke et al., 2020). In this way, the extent of the fitness between practical challenges and generated knowledge can be determined. In this dissertation, two forms of design knowledge have been produced. On the one hand, detailed DPs that can be used for the construction of AI-based solutions were represented as virtual agents or embedded into user interfaces. On the other hand, aggregated design knowledge in the form of design patterns have been developed based on detailed design knowledge. The evaluation results concerning the DPs in the articles indicate that the instantiated design knowledge helps SEs perform hybrid online service delivery on resource-efficient ways and supports SKs' provision of relevant information. However, a higher level of projectability of the design knowledge could have been achieved if the DPs had been materialized in different companies in both application domains. Furthermore, longitudinal evaluation procedures could have helped in determining the overarching impact of the implemented artifacts at the departmental and organizational levels. In terms of evaluation strategy, the generalizability of performed assessment steps is limited due to the simulation of SKs. The evaluation of detailed design knowledge in the form of DPs depends on the methods used and the data produced. To address the validity limitations, the articles focused on a mix of methods and data. Subjective data could thereby be obtained using standardized survey instruments (e.g., questionnaire items). To counteract self-report bias, objective usage data were collected to supplement the subjective data and to support the interpretation of the overall results. Regarding aggregated design knowledge, the presented design patterns are suitable for projection in future projects owing to their abstractness. However, the design patterns have not yet been validated. Nevertheless, as the underlying DPs have been confirmed in their fitness, it can be presumed that the design patterns are suitable for addressing the described environmental challenges.

8 Implications for Further Research

Based on the findings, this cumulative dissertation provides an outlook for future research. Taking into account the multiple perspectives on AI management, service and work (re)design, and interaction design, these avenues for future research refer to the integration of AI into online service delivery work systems and the interaction design of AI.

8.1 Integration of AI into Online Service

As a continuation of the study by Poser and Bittner (2021) on the socio-technical integration of AI in online service delivery work systems, the focus on involving employees in determining the application of AI could be intensified. Accordingly, the participation of employees in the specification of the future of work scenarios could extend beyond their input in terms of communicating existing problems and improvement potential. In keeping with M. M. Li et al.'s (2022) results on low-code development platforms as a method for employees to proactively influence job design, the impact of this form of job crafting should be evaluated in the future. For this purpose, case studies and empirical investigations on the effects of self-developed CAs for self-service on employees (e.g., well-being, satisfaction, and meaningfulness) and companies (service quality and efficiency) should be conducted.

In the future, the perspective on and requirements for the role of AI in hybrid service delivery of SKs should also be captured. In this dissertation, the identification of challenges and problems is focused on processes and tasks on the side of the service provider. To capture 360-degree feedback to describe as-is situations and to verify the planned integration of AI, SKs' perspectives in the form of generalized demands and improvement potential should be considered. In doing so, the impact of AI-based solutions and handover scenarios as part of automated and augmented service encounters on SKs' service experiences should be addressed. Therefore, to perform this kind of evaluation, suitable approaches and methods have to be identified. In this context, the criteria set of Lewandowksi et al. (2023) could be applied and extended to assess the quality of CAs for the automation of service encounters from the perspective of SKs. To evaluate augmented service delivery with AI-based solutions from the perspective of SKs, a catalog of quality criteria is still needed.

Also related to the integration of AI, the advantages and disadvantages of implementing hybrid online service delivery as part of automation or augmentation strategies or their combination should be studied in more detail in the future. Thus, the design knowledge produced in this dissertation can be used to establish synergy between the automation and augmentation of online service encounters. By integrating AI into the environment (e.g., enterprise), insights into the effectiveness of each strategy, compared to a combination of strategies, can be gained. For this approach, the results related to the design knowledge of this dissertation can be used to explore different forms of integration with hybrid service processes and tasks using AI-based solutions that are represented as virtual agents or embedded in user interfaces and designed for this purpose. The emerging results could produce insights into the effective management of AI in the online service context.

As an extension of the customer service and internal IT support application domains considered in this dissertation, future research could address the structural, process-, and task-related aspects of similar service domains across industries. By generating descriptive knowledge on similarities of widespread intangible online service delivery within or across enterprise boundaries, general potential and threats for integrating AI into these related work systems could be achieved. Furthermore, in keeping with Davenport and Ronanki (2018), who found that companies often apply AI solutions to internal IT support before adapting them for customer service owing to their similarities, AI implementation strategies for companies could be described.

8.2 Design Knowledge for AI-infused Hybrid Online Service

In this cumulative dissertation, existing infusion archetypes were extended to determine the socio-technical interdependencies between AI, SK, and SE. The resulting interaction design knowledge can be used to produce AI-based solutions for automating service encounters. In addition, the generated design knowledge can be used to construct handovers and the augmentation of encounters with AI that is invisible to SKs. Future research should investigate the infusion archetype, whereby AI augments the interaction in a visible way for SKs. This research should determine for which service requests this form of augmentation makes sense. Furthermore, the interaction should be determined in terms of the representation and behavior of the AI. In this context, the extent and visual representation of AI's proactivity and reactivity should be determined by considering the requirements of both SKs and SEs.

Another topic that should be further explored in future research is the delegation principles between AI and SE in the form of handovers. In this dissertation, handovers from CAs to SEs were investigated as a service recovery strategy in the context of hybrid consecutive online encounters. As a continuation of this, the question of whether handovers to SEs should be visible to SKs can be investigated. Previous findings indicate that the failure of self-service technology has an adverse effect on SKs (Mozafari et al., 2021); therefore, future handover solutions in which SEs take control of the back end of a CA in a way that is invisible to SKs could be produced. In addition to creating a suitable user interface with and as an extension of the presented design knowledge in this dissertation, there is a need to define mechanisms and processes that allow SEs to monitor and take over the conversation of CAs before it breaks down. Furthermore, the influence of visible and invisible handovers on the satisfaction of SKs with the service experience and of SEs with this form of hybrid online service delivery should be analyzed in a naturalistic evaluation setting. In addition, further forms of handovers in online service encounters in which AI and SE mutually delegate activities to be performed for the processing of the request should be investigated.

An additional subject for future research is the extension of design knowledge for HISs. In this dissertation, design knowledge for two forms of AI appearances has been produced. Because there has been a limited knowledge base for the design of HISs, the generated knowledge can provide a starting point for the exploration of a suitable appearance of AI for hybrid simultaneous online service encounters. More specifically, future research should compare HISs with AI represented as a virtual agent and AI embedded in a user interface to investigate the advantages and disadvantages of each representation for SEs. In this context, the extent to which the humanlike representation and behavior of AI has a positive impact on SEs could be investigated. An additional aspect for future research is the adaption of human-AI interaction in HISs to the needs of users with different characteristics. In the context of online service delivery, SEs provide SKs with information and/or solve problems. As the effort associated with executing these activities varies with experience level and human abilities are limited in terms of processing information in complex tasks, descriptive knowledge should be used to produce user interface configurations to provide individual support for SEs with different experience levels.

9 (Re)Designing IT Support: How Embedded and Conversational AI Can Augment Technical Support Work

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Abstract

Striving for operational efficiency and cost-effectiveness, companies increasingly deploy artificial intelligence (AI). This trend also incrementally permeates service-related work in technical support. As current narrow AI cannot fully substitute service employees and greater effects are achieved with hybrid service delivery, adapted work settings are required. Based on a qualitative field study with a socio-technical approach, this research provides current problem scenarios in IT support and a support process redesign by integrating conversational and embedded AI. The study contributes evaluated insights about current work processes, work-related issues, and a hybrid IT support process that introduces substitution and augmentation of human tasks to improve service delivery.

Keywords: Conversational AI, embedded AI, work (re)design, socio-technical, technical support, IT support

9.1 Introduction

The digitalization of data and rapidly expanding capabilities of Artificial Intelligence (AI) have led to an increased deployment of AI-powered technology across industries (Brynjolfsson et al. 2018; Østerlund et al. 2021). In particular, the advent of sophisticated Machine Learning (ML) techniques facilitates organizations' efforts to elevate value and revenue growth through increasing their efficiency and effectivity with automated business processes and activities (Lacity and Willcocks 2016; Lu et al. 2020). In this way, AI-enabled automation technology is disrupting and transforming the execution and organization of knowledge-intensive work in organizations by taking over tasks and activities (e.g., response generation, prediction) (Faraj et al. 2018; Grønsund and Aanestad 2020).

This transformative process is also evolving in the service context. Appearing as AI-enabled agents or embedded algorithms and being capable of making decisions (Glikson and Woolley 2020), ML-based AI is utilized by organizations to cost-effectively, consistently and efficiently deliver information-rich and time critical service (Bock et al. 2020; Keyser et al. 2019; Larivière et al. 2017). A common application area for these types of AI, is technical support (Lu et al. 2020). This knowledge-intensive service delivery work includes fast-paced information provision, advice and problem solving for users' complex technical products (e.g., software) in lower hierarchy support levels (Das 2003; Shaw et al. 2002). By implementing AI-enabled agents or embedded algorithms, an increasing number of recurring and standardized service inquiries with information content output can be automatically processed. This form of service delivery automation substitutes tasks previously performed by service employees and can contribute toward reduced resolution times for inquiries. One such example is Amelia, a digital employee for the internal IT support of SEBank. During deployment, this AI-enabled agent successfully generated solutions or provided suitable information in a dialog-based interaction for the majority of 4,000 inquiries from 700 employees (Davenport and Ronanki 2018; SEBank 2016).

Despite the potentials of AI, service delivery in technical support work cannot be fully automated in the foreseeable future due to the use-case specificity of present narrow or weak AI (Ostrom et al. 2019; Raj and Seamans 2019). In addition, recent research indicates that combining the capabilities of humans and AI instead of solely substituting human tasks can provoke substantial increases in performance at the organizational as well as individual level (Østerlund et al. 2021; Wilson and Daugherty 2018). Accordingly, work settings should facilitate, both, the work of employees and AI side-by-side and their collaborative interplay (Makarius et al. 2020; Paluch and Wirtz 2020; Seeber et al. 2018). To achieve these performance-enhancing work conditions, a hybrid task-based division of labor needs to be established, which promotes the strengths of AI and employees to compensate the limitations of the other (Benbya et al. 2021; Dellermann et al. 2019; Østerlund et al. 2021). This requires an in-depth understanding of existing work practices in order to identify suitable tasks for AI-based substitution and augmentation on a business operation level (Lacity and Willcocks 2016). As human work should remain the scaffolding for AI-integrated technical work (Wolf and Blomberg 2019), a socio-technical holistic approach is required that considers work process requirements and employees' work-related needs to adapt task division and redesign processes (Alter 2013; Makarius et al. 2020). However, the integration of AI and human work processes is not yet well developed (Benbya et al. 2021; Larivière et al. 2017; Makarius et al. 2020). Furthermore, the adoption of socio-technical approaches to capture work systems in their entirety and address the needs of service employees is scarce (Alter 2020; Lu et al. 2020). As purposeful substitution and augmentation of human tasks with AI could facilitate time-critical service delivery in lower hierarchy support, this paper addresses these knowledge gaps by proposing a socio-technical perspective on a hybrid task division between service employees and AI. Consequently, we address the following research question:

RQ: *How to integrate AI into IT support work by (re)defining processes and task division?*

This question is addressed by examining intra-company IT support as a relevant class of technical support, as it represents a pervasive form of service delivery in organizations with a high request frequency (Schmidt et al. 2021). According to Design Science Research (DSR), the study at hand makes a two-fold contribution of knowledge by presenting, both, an analysis of the problem space and its context as well as of a solution space by deriving possible solutions for the addressed application domain (Hevner et al. 2004; Vom Brocke et al. 2020). More specifically, we describe current work processes and identify and locate work-related issues. In addition, a renewed IT support process model and hybrid task division with embedded and conversational AI is proposed and evaluated. The paper is structured as follows. First, we present related work on technical support and AI in service. Second, we describe the research design and methodological approach. Following this, we present the results of the qualitative content analysis in the form of an as-is situation with work-related challenges and a to-be solution with an integration of AI. We discuss evaluation results of the as-is situation and to-be solution. Finally, we outline implications, contributions, limitations, and opportunities for future research.

9.2 Related Work

9.2.1 Technical Support Work

Technical support is provided by organizations for external or internal users and comprises maintenance, problem solving and advice-giving activities for hardware and software (Das 2003). It is a post-sales service for end-users of a primary technology product or service (van Velsen et al. 2007). By improving external customer loyalty and brand image, this service provision can result in economic advantages for companies, e.g. revenue growth (Davenport and Klahr 1998). In organizations, the provision of IT-related support for internal end-users is a form of technical support work growing in importance and volume. As organizations increasingly invest in and rely on IT infrastructure to foster productivity (González et al. 2005), IT departments' task portfolio has shifted from system development to service provision and maintenance of a sustainable and stable IT infrastructure (Sauve et al. 2006). These IT-related services, which we refer to as IT support, include answering end-users' questions, assisting with the integration of IT into the working environment, installing software and hardware as well as resolving problems (Shaw et al. 2002). According to Technical Support Work Theory (Das 2003), this work comprises four general problem-solving activities. To process requests from end-users, support employees (1) locate individual knowledge or retrievable information, (2) adapt existing solutions to resolve similar requests, (3) generate solutions to an unknown problem by experimentation or (4) escalate the request to a more specialized unit. The guiding principle for these tasks is to ensure end-users' error-free use of IT by providing high quality, efficient and immediate support (Kajko-Mattsson 2004). To deliver and coordinate service in a timely and cost-efficient manner, companies utilize established processes and units, which are often hierarchically organized (Agarwal et al. 2012; Galup et al. 2009; Marrone and Kolbe 2011). In the frontstage, service employees of the 1st support level attempt to find solutions in the shortest possible time after receiving requests via help desk, telephone, e-mail, or a web-based form (Barash et al. 2007; Prifti et al. 2014). Different activities are carried out for incident (error-related requests) and request management (e.g., end-user questions) that involve, inter alia, the documentation and assignment of requests, communication of information, execution of initial diagnoses and, if possible, creation of solutions (Jäntti et al. 2012; Kumbakara 2008). If end-users' requests are too complex, they are documented and escalated to higher, more specialized backstage support groups comprising 2nd and 3rd support level (Kajko-Mattsson 2004; Simoudis 1992). Employees in the 2nd support level execute repairs, modifications or reassignments to the highest support level if no solution can be implemented (Barash et al. 2007).

Hence, IT support work is characterized by time-critical, knowledge-intensive activities and a distribution of interdependent tasks across hierarchically separated units (Gray and Durcikova 2005). Research has shown that the successful execution of problem-solving activities is oftentimes impeded, because support employees face the challenge of determining the scope and context of requests as they are confronted with a broad spectrum of questions and problems from end-users (González et al. 2005). In addition, the plethora and complexity of IT systems intensify the demand for specialized knowledge (Eschenfelder et al. 1998; Schmidt et al. 2021). Therefore, employees' capabilities to process requests are commonly exceeded and relevant coworkers' knowledge and information resources are distributed across the organization (Das 2003; Gray and Durcikova 2005). To increase the efficiency of IT service delivery, previous research proposed to focus on the potentials of AI applications (Østerlund et al. 2021). AI has been investigated to elevate the effectiveness of process-controlled service delivery tasks (Mandal et al. 2019). Moreover, AI solutions have been developed to enhance the activities locate and adapt by improving access to knowledge resources in the organizational environment (Graef et al. 2020; Schmidt et al. 2021). Thereby, previous studies investigated single AI solutions addressing segments of the service delivery process. However, a holistic consideration of the service process, interdependence of process steps and activities to promote cross-hierarchical service delivery in connection with AI has so far been disregarded.

9.2.2 Artificial Intelligence and Service

AI introduces fundamental changes in service (Huang and Rust 2018; Østerlund et al. 2021) and is defined as „the configuration of technology to provide value in the internal and external service environments through flexible adaptation enabled by sensing, learning, decision-making and actions" (Bock et al. 2020, p.319). The underlying technologies, e.g., ML, are categorized as constituents of narrow AI (Bock et al. 2020; Davenport et al. 2020). This current form of AI is able to interpret large amounts of data, recognize patterns and generate results in the form of knowledge or action, e.g., by influencing other systems or autonomously executing tasks (Davenport et al. 2020; Kaplan and Haenlein 2019). In contrast to traditional rule-based, deterministic automation, ML-based AI infers probabilistic outcomes based on existing data and can continuously improve through learning strategies (Ghahramani 2015; Glikson and Woolley 2020; Lacity and Willcocks 2016; Raj and Seamans 2019).

Implementing AI in service affects the organization, customers and employees and thereby transforms the service production (Keyser et al. 2019; Østerlund et al. 2021; van Doorn et al. 2017). In particular, AI reshapes technology-mediated service delivery that focuses on intangible actions (e.g., information provision) for individuals (Lovelock 1983; Wirtz et al. 2018). In such virtual service environments, customers and service employees are confronted with different AI appearances. On the one hand, AI-enabled agents (e.g., conversational agents (CAs), smart personal assistants) are virtually represented and facilitate user interaction via natural language. These agents communicate in a human-like fashion via written or spoken language and act autonomously to assist users during a task (Knote et al. 2019). On the other hand, embedded AI constitutes algorithms without visual representation. Being invisible to users, these algorithms are integrated in various software applications such as search engines or knowledge repositories (Glikson and Woolley 2020). These AI appearances cause modified interactions between company and customer in the frontstage and internal service provision processes and tasks in the backstage (Bock et al. 2020; Larivière et al. 2017; Marinova et al. 2017).

To deploy AI in service, connections between task-relevant input and outputs need to be established (e.g., matching customer problems to solutions from the past). After training with data sets, most probable outputs can be predicted by ML-models for similar input by relying on these input-output relationships (Brynjolfsson et al. 2018; Krogh 2018; Levy 2018). Therefore, AI can be implemented to automate repetitive low-complexity tasks with high input volume and few exceptions for output. In addition, tasks with high input volume and high output variability, regarded as average-complexity tasks, can be supported by AI (Crowston and Bolici 2019; Traumer et al. 2017). Based on these capabilities of AI, service work can be restructured by substituting employees' tasks or augmenting employees' competences with AI for simultaneous hybrid task accomplishment (Rai et al. 2019). In the frontstage, service delivery demands varying degrees of cognitive and emotional involvement (Wirtz et al. 2018). AI-enabled agents, e.g. CAs, can substitute standardized tasks with low emotional and cognitive complexity without direct involvement of service employees (Ostrom et al. 2019). Moreover, AI-enabled agents are increasingly capable of substituting consistent, predictable and information-intensive tasks with low emotional but high cognitive complexity in the frontstage (Paluch and Wirtz 2020). For these use cases, CAs are often used as a service interface to provide problem solving advice and answer well-established (FAQs), fact-based or data-intensive requests from customers (Belanche et al. 2020; Følstad and Skjuve 2019; Levy 2018). Tasks requiring high emotional and cognitive involvement are suitable for augmentation of service employees' emotional capabilities with the analytical power of AI. In addition, AI can assist service employees by guiding encounters and identifying customers' emotions or providing interaction-specific supplementary information (e.g., customer history) (Amorim et al. 2019; Kuramoto et al. 2018; Povoda et al. 2015). For backstage tasks, embedded AI can augment the execution of processes and task-work activities (Crowston and Bolici 2019). The processing and resolution of requests can be facilitated by embedded AI displaying similar documented cases from the database for a current task (Graef et al. 2020; Mandal et al. 2019).

In these prior studies, service delivery efficiency, cost and waiting time reductions for customers have been addressed by referring to different use-case scenarios for AI. In this regard, different forms of substituting and augmenting service employees' front- and backstage tasks have been investigated focusing on automating aspects of the service production from an organizational perspective (Lu et al. 2020). However, to fully exploit the potential of AI, bottom-up approaches are required to identify processes and tasks afflicted with challenges for service employees that can be alleviated with AI (Lacity and Willcocks 2016).

9.3 Research Approach

We follow the DSR paradigm to contribute to the solution of relevant and prevalent real-world problems for a defined application domain (Hevner et al. 2004). More specifically, we contribute to the body of knowledge with a hybrid division of tasks to alleviate work-related issues in IT support. In doing so, we create a representation of the problem space and lay the foundation for possible solutions in the form of socio-technical artifacts (Gregor and Hevner 2013; Vom Brocke et al. 2020). We adopt the Digital Work Design (DWD) approach by Richter et al. (2018), which proposes a bottom-up analysis of work practices to elicit issues (as-is situation) in order to design work environments with a socio-technical focus by reducing work-specific problem scenarios (to-be solution). To guide the derivation of the as-is situation and creation of the to-be solution, we follow the procedure of process (1) discovery, (2) analysis, and (3) redesign proposed in the BPM Lifecycle Model (Dumas et al. 2015). Overall, our research process spans five steps (see Figure 1).

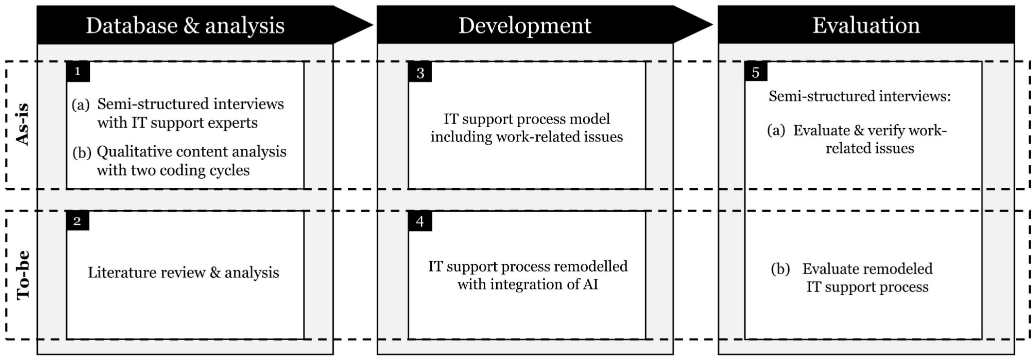

Figure 1. Research Process

Database creation and analysis: To reach profound insights into the as-is situation, we conducted a cross-sectional qualitative field study with multiple organizations (Edmondson and Mcmanus 2007). We executed an interview-based discovery of IT support processes and associated work-related issues to uncover similarities across contexts (step 1 | activity a). A purposeful sampling strategy was applied with boundary criteria to select organizations and participants. First, companies have an IT department and a total workforce of at least 200 employees. We assume that this size ensures a critical mass of incoming support requests. Second, IT support departments are situated on organizational premises and concerned with promptly restoring IT service for knowledge intensive work. With this focus and the exclusion of production-related support, we aim to achieve comparability of organizational contexts. Third, interviewees need to have in-depth knowledge about general support procedures as well as specific process steps and tasks in the lower levels of the IT support hierarchy. Therefore, employees were contacted who manage IT departments or work for the 1st and 2nd level IT support. Semi-structured interviews were conducted with 13 employees performing various functions across hierarchical levels in eight IT support work contexts (see Table 1) (Myers and Newman 2007). An interview guide with open-ended questions was created to cover relevant topics and allow interviewees to address certain aspects more thoroughly. The guide comprised (1) an introduction to the research project, (2) presentation of the company, role, and responsibilities by the interviewee (e.g., “What are your job duties, daily tasks and primary responsibilities?”), (3) description of the IT support process as well as associated tasks (e.g., “How does the IT support process look like, how are requests handled?”) and (4) characterization of problem scenarios and challenges connected to the process and tasks (e.g., “To what extent do challenges exist and for which process steps or tasks?”). The interviews lasted 46-85 minutes, were conducted via video call from June to October 2020 and recorded with the permission of the interviewees. Verbatim transcripts were prepared for the subsequent data analysis. The reliability of the data gathering process was established with a protocol (interview guideline and data collection modalities) and a database comprising transcripts, notes, and documents.

To conduct thorough analyses of IT support processes and uncover work-related issues (step 1 | activity b), we performed a rigorous qualitative content analysis of interview transcripts with MAXQDA 2020. We applied a multi-cycle process using a deductive-inductive approach (Miles and Huberman 1994; Saldaña 2013). We used two coding methods in the first cycle. First, “descriptive coding” was performed with deductively derived a priori codes. Using Das (2003) Technical Support Work Theory, we coded problem-solving activities (locate, adapt, generate, escalate) for the different IT support levels. Second, using the “initial coding” method, text segments, which could not be assigned to deductive codes, were approached with open and inductive coding. Thereby, codes with reference to the process and work-related issues across support levels emerged (e.g., additional mental investment). In the second coding cycle the pattern coding method was applied to reach a higher level of abstraction and derive themes (Saldaña 2013).

Conceptually matching codes were merged and categories were formed, resulting in six categories (e.g., access to knowledge) and 15 subcategories (e.g., knowledge traceability) related to work-related issues. Furthermore, three process-related categories (e.g., frontstage activities) with five subcategories referring to tasks (e.g., request processing) were generated and matched with problem-solving activities from the first cycle. Validity was established by harmonizing codes of multiple researchers through constant exchange.

Table 1. Overview of IT Support Contexts and Interviewees

Interviewee	**Industry**	**Company size (personnel in k)**	**Interviewee position**	**Interview duration**
I1	Mobility	5-25	Frontstage / 1st Level IT Support	71 min.
I2			Backstage / 2nd Level IT Support	55 min.
I3	Education	5-25	Frontstage / 1st Level IT Support	46 min.
I4			Teamlead IT Support (1st)	60 min.
I5	Commerce	0.25-5	Frontstage 1st Level IT Support	67 min.
I6			Teamlead IT Support (2nd)	60 min.
I7	Insurance	0.25-5	Frontstage / 1st Level IT Support	69 min.
I8			Backstage / 2nd Level IT Support	57 min.
I9	Media	5-25	Teamlead IT Support (1st)	51 min.
I10			Head of IT Infrastructure	
I11	Automotive		Teamlead IT Support (2nd & 3rd)	48 min.
I12	Commerce	0.25-5	Backstage / 2nd Level IT Support	70 min.
I13	Healthcare	0.25-5	Frontstage / 1st Level IT Support	85 min.

For step 2, we conducted a literature search following the principles of Cooper (1988) and Webster and Watson (2002) to determine the scope and structure of the search process. To identify AI solutions for technical support work with focus on IT support that pertain to the work-related issues from step 1, we searched for peer-reviewed English publications in the databases of ACM Digital Library, IEEE Xplore, AIS eLibrary and EBSCOhost Business Source Complete. In line with this objective, we utilized varying combinations of the following keywords: “IT support”, “help desk”, “IT service”, “automation”, “artificial intelligence”, “AI”, “machine learning”, “ML”. In the screening phase we reviewed titles and abstracts and excluded publications which deviated from the search objective with a focus on (1) other fields than service or (2) support for production (machines). We selected 18 publications, which cover AI instantiations or concepts, by categorizing them according to the six code categories of work-related issues from step 1 (detrimental characteristics of tasks, knowledge access, missing user information, variety of contact channels, request characteristics and escalation) and their form of appearance (AI-enabled agent, embedded AI).

Development: For the development of the as-is situation (step 3) and to-be solution (step 4) (see Figure 1), the process modeling technique Business Process Modeling Notation

(BPMN) was used, as it is, inter alia, suitable for the representation of service provision processes consisting of process-related steps and activities while considering the customer and different groups of organizational actors (Dumas et al. 2015; Milton and Johnson 2012). As part of step 3, we created a unified IT support process incorporating identified work-related issues for the as-is situation. To model this process and define issues, we used insights from step 1. For step 4, a process redesign was executed to address the identified issues with AI solutions from the body of knowledge (step 2).

Evaluation: To assess the validity, applicability, suitability, and level of completeness of the developed processes in step 3 and 4 (Hevner et al. 2004), we conducted semi-structured interviews with three additional domain experts via video calls. These experts from different IT support work contexts (department manager for 1st and 2nd level IT support (EI1), 1st level (EI2), and 2nd level (EI3) IT support employee) were identified through referral of interviewees from step 1. After the presentation of context information about the study as well as the content and process depictions of the as-is situation and to-be solution, discussions were guided by four open-ended questions (representativity of as-is process; representativity of work-related issues; expected improvement of task work with AI; usefulness and feasibility of AI integration). By deductively analyzing transcripts according to the four themes of the interview questions, we examined the verification of the as-is process model with issues (step 5 | activity a) and a plausibility and potential analysis of the reengineered process (step 5 | activity b).

9.4 Development

9.4.1 As-is Situation

By consolidating characteristics of the examined IT support contexts, we present the as-is situation with a unified IT support process including steps and tasks. In addition, work-related issues are described and located in the process.

IT support process: In line with literature (e.g., Kumbakara (2008)), the process analysis revealed that all eight IT support contexts have hierarchically organized support levels consisting of frontstage (1st level) and backstage (2nd and 3rd level) divisions. The level of technical specialization intensifies per hierarchy level. The number of employees in the 1st level and specialized units in the 2nd and 3rd level increases in relation to the size of the company and number of serviced users. In the investigated IT support contexts, four channels are provided to contact IT support: e-mail, web-interface, telephone, chat. Support seekers use the e-mail and web interface channels most intensively followed by personal contact on the phone. With reference to the tasks (see Figure 2), the process analysis showed that the 1st level receives requests from support seekers, documents and analyzes them. Requests that cannot be solved ad hoc by locating suitable knowledge items, are enriched in documentation and escalated to a queue of a specialized backstage unit in the

2nd level. Previously documented tickets are analyzed, to use or adapt an existing solution or a new one is generated. The solution is sent to support seekers via the 1st level. If a solution cannot be created, the ticket documentation is extended with eliminated sources of error and escalated to the highest unit in the hierarchy (3rd level). In this level, in-depth analyses, modifications, and development are performed to resolve a problem. Implemented changes are directly communicated to support seekers. As part of the different tasks across hierarchy levels, the analysis showed that support employees perform the four basic problem-solving activities (locate, adapt, generate, escalate) according to Das (2003) to varying degrees. 1st level employees either perform the *locate* activity as part of finding existing solutions or *escalate* requests. 2nd level employees *locate* existing solutions during their search and mainly *adapt* them, *generate* new solutions or *escalate* requests. Similarly, 3rd level employees *adapt* but primarily *generate* new solutions.

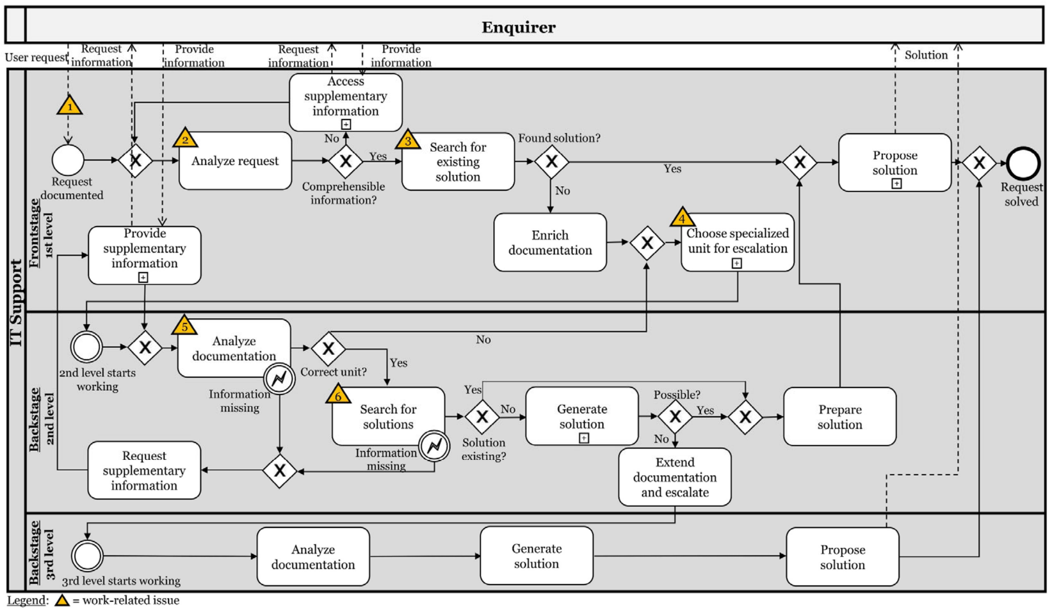

Figure 2. As-is Situation

Work-related issues: Along with process-related findings, we identified six work-related issues that are associated with tasks in the front- and backstage across IT support work contexts (see Figure 2 & Table 2). In the frontstage, the large volume of requests causes challenges for 1st level employees. A substantial proportion of these requests represents "day-to-day business and is solved easily" (I7) but requires a lot of time to process. In this regard, I6 reports from the perspective of a team leader that "recurring standard requests reach them, they copy and paste the e-mail they sent to someone else, substitute the name and hit reply". This is the "main issue and what causes a lot of effort, because you do not only have to handle two problems a day - it is the quantity" (I1). As a result, service employees are strained in patience and perseverance, which reduces their time to deal with complicated issues. The volume of requests can temporarily inhibit immediate service provision for support seekers. Furthermore, structured processing is impeded because support seekers request help via various channels. **Issue 1**: *Large numbers of simple and* *recurring requests distributed over various channels hamper systematic processing and reduce time and cognitive resources for complex matters*.

In addition to the high quantity, content quality of requests is frequently inferior. Requests are unstructured, incomplete, lack detail, and relevant information (e.g., screenshot, error description). “The user usually does not know what exactly the problem is and does not know how to describe it and what information to give” (I5). Moreover, support seekers have difficulty describing their request in a comprehensible form. This makes problem analysis more difficult for 1st level employees, as described by I7: “You have to check if you know what the end users mean, if not, call them, then create documentation afterwards”. Repeated contacting and re-qualification of requests imply additional expenditure of time. “If we had all this already, we would not have to annoy the user with it on the phone or in written correspondence. This would significantly speed up the processing of requests” (I3). **Issue 2**: *Insufficient and unstructured information from support seekers impedes problem analysis and prolongs request processing due to repeated contact to support seekers*.

To process requests, employees in the 1st level search for documented knowledge in the form of existing solutions. This activity is associated with the challenge of promptly detecting suitable knowledge. “The biggest impediment is actually the mass of information, to find the right one” (I5). From a team leader perspective, I4 describes: “The more there is, the more difficult it is to find something. Sometimes it is just as complicated to find the right one out of thousands of entries as it is when there is none”. The search process is cumbersome, and time consuming, as unique search terms are required to receive relevant hits and not all document types are searched. In addition, documented knowledge often comprises “outdated problem issues that have ceased to be useful” (I13). Thus, employees must invest effort to find solutions via alternative sources (e.g., using publicly accessible internet sources). **Issue 3**: *Untraceable task knowledge and existing knowledge with missing task reference require investment of additional cognitive and time resources for the search process.*

Due to untraceable knowledge, 1st level employees have difficulty determining if and when requests should be escalated. “This aspect is a fundamental problem in the daily work of an IT support employee – deciding at an early stage, can I solve the problem? Should I escalate the request? Is there a documented solution to it?” (I13). Time constraints cause decision-making pressure, which results in requests being escalated too early despite existing documentation of a suitable solution. In addition, based on the request content, 1st level employees have difficulties identifying suitable units in the 2nd level which are specialized for thematic areas. Thus, requests are routed to the wrong backstage unit. A large proportion of these requests are returned from the 2nd level units. “Then it is up to the 1st level to figure out where the request really needs to go” (I11). Accordingly, “making information easier to retrieve with keywords would assist support employees at this point” (I10) and reduce additional work steps for 1st and 2nd level employees. **Issue 4**: *Lack of* *decision support for escalation of requests and identification of eligible experts causes additional work steps.*

A work step preceding the escalation of requests is the documentation of the initial analysis and conducted problem-solving steps by a 1^{st} level unit. The quality of this documentation is volatile. Reports are commonly erroneous and do not comprise required information such as “Who am I? Which release version of the software does it concern? Which component, which processes? A small description of the request in prose” (I2). Consequently, “additional work emerges for the 2^{nd} level, because we do not understand the nature of the problem” (I12). Therefore, 2^{nd} level employees must “return it with comprehension and consolidation questions” (I8) to the 1^{st} level. “This can extend the processing of a request from two to ten minutes, for example” (I12), causing additional work steps for 1^{st} level employees when requests are returned: “We review the tickets again, contact the user again, re-qualify the tickets and then return them to the specialized unit” (I5). **Issue 5**: *Information-poor documentation of escalated requests causes additional work steps and prolongs continuation of processing.*

Request processing is complicated by inaccessible solution knowledge, since “hardly any documentation” (I12) exists. “Many support teams operate their own systems. Whether that is a wiki, database, or whatever” (I11). Accordingly, 2^{nd} level employees have to develop a solution, although colleagues might have a well-documented solution to the problem. Thus, a considerable amount of time and cognitive capacity is spent on searching (“you have to know to which keyword a subject is connected” (I11)), extending and updating a personal repository. Consequently, employees struggle as there is no defined standard “until where my error analysis continues and when I should stop to invest time and energy to generate a solution” (I8). **Issue 6**: *Inaccessible task knowledge and a limited knowledge base demand additional cognitive and time resources to generate solutions and expand the personal knowledge documentation.*

Table 2. Frequency of Work-related Issues across IT Support Contexts

<table>
<tr><th>IT support division</th><th>Issue</th><th>Numbers of support contexts affected</th><th>IT support division</th><th>Issue</th><th>Number of support contexts affected</th></tr>
<tr><td rowspan="4">Frontstage (1^{st} level)</td><td>1</td><td>5/8</td><td rowspan="4">Backstage (2^{nd} level)</td><td rowspan="2">5</td><td rowspan="2">6/8</td></tr>
<tr><td>2</td><td>7/8</td></tr>
<tr><td>3</td><td>7/8</td><td rowspan="2">6</td><td rowspan="2">6/8</td></tr>
<tr><td>4</td><td>5/8</td></tr>
</table>

9.4.2 To-be Solution

Identified work-related issues for IT support indicate intensive workload that overstresses service employees’ limited capacities for information processing activities. Using the results of the literature search, we describe anticipated effects of AI solutions to reduce work-related issues in lower IT support levels and present their functionalities (see Table

3, 4). To minimize performance deterioration as well as support and relieve employees, we propose a remodeled IT support process with a hybrid division of tasks between AI and service employee (see Figure 3).

Frontstage: AI-enabled CAs can generate improvements by substituting tasks of 1st level employees. Depending on the availability and quantity of training data, CAs can record and/or solve service requests and problem reports automatically (e.g., Fiore et al. 2019; Meyer von Wolff et al. 2020). As a result, the percentage of requests that need to be handled by employees can be significantly reduced (Alter 2020). In addition, service employees' subsequent analysis of requests can be improved, as richness of information can be achieved via a fine-grained documentation of input (e.g., Gupta et al. 2009). This reduces the need for repeated contacting of support seekers. Under consideration of the dependency of allocated (sub-)tasks, intermediate results of CAs should be handed over to 1st level employees to promote an effortless continuation of processing (Poser et al. 2021) (***Issue 1 & 2***). The integration of embedded AI into relevant systems, e.g., ticketing tools, can augment 1st level employees' work by reducing their effort to find or generate solutions (Dasgupta et al. 2014). The recommendation of effective and efficient solutions preserves 1st level employees' time and cognitive resources. In addition, the traceability of knowledge can be promoted and the "vocabulary problem" due to search-term sensitivity is reduced (Müller et al. 2016) (***Issue 3***). As the increase of erroneous routings significantly extends the total processing time (Agarwal et al. 2012; Shao et al. 2008), 1st level employees should be augmented in documenting and transferring tickets. Embedded AI can assist in mitigating service employees' strain to promptly identify experts and reduce avoidable work steps resulting from misrouted tickets by proposing suitable groups or employees in the 2nd level (***Issue 4***).

Backstage: Embedded AI may also yield positive effects by augmenting 2nd level employees. AI-based evaluation of the quantity and quality of free-form text (e.g., minimum word count, automatically derive categories) from 1st level employees prior to escalation could improve subsequent analysis by 2nd level employees (***Issue 5***). Furthermore, by proactively mining and presenting semantically similar knowledge items with structured descriptions, diagnostic steps, and resolution activities, the investment of time and cognitive resources in the search process for and generation of solutions and the development of individual knowledge bases could be reduced (***Issue 6***).

Table 3. AI Solutions for the Frontage

<table>
<tr><th></th><th>Issue</th><th>Appearance</th><th colspan="2">Description of functionality</th><th colspan="2">References</th></tr>
<tr><td rowspan="5">**Frontstage**</td><td rowspan="2">**1**</td><td rowspan="2">AI-enabled agent</td><td>*Limited amount of training data:*
Answer FAQs with text analytics by automatically mapping support seekers' descriptions to problems and associated solutions</td><td rowspan="2">Dispatch requests including documentation to 1st level employees if not solved</td><td>**I:** (Dasgupta et al. 2014; Gupta et al. 2009; Silva et al. 2018)</td><td rowspan="2">**I:** (Agarwal et al. 2012; Shao et al. 2008);
C: (Müller et al. 2016)</td></tr>
<tr><td>*Extensive training data:*
Answer requests beyond FAQs, handle service-related requests (e.g., password reset), trouble-shoot problems</td><td>**I:** (Fiore et al. 2019; Subramaniam et al. 2018; Vinyals and Le 2015);
C: (Alter 2020; Thorne 2017)</td></tr>
<tr><td>**2**</td><td>AI-enabled agent</td><td colspan="2">Document requests in dialog by means of a fine-grained categorization of input</td><td colspan="2">**I:** (Acomb et al. 2007; Kadar et al. 2011)</td></tr>
<tr><td>**3**</td><td>Embedded AI</td><td colspan="2">Proactively present high-quality solutions or solution steps of similar problems by deploying text mining, knowledge representation methods or a case-based reasoning approach</td><td colspan="2">**I:** (Graef et al. 2020; Potharaju et al. 2013; Zhou et al. 2017)</td></tr>
<tr><td>**4**</td><td>Embedded AI</td><td colspan="2">Determine suitable groups or employees in the 2nd level with text analytics based on ticket content and escalate when a pre-defined threshold is met</td><td colspan="2">**I:** (Agarwal et al. 2020; Mandal et al. 2018)</td></tr>
<tr><td colspan="7">**Note: I** = instantiation; **C** = concept</td></tr>
</table>

Table 4. AI Solutions for the Backstage

	Issue	Appearance	Description of functionality	References
Backstage	**5**	Embedded AI	Evaluate the quantity and quality of free-form text with text analytics	**I:** (Potharaju et al. 2013); **C:** (Müller et al. 2016)
	6	Embedded AI	Proactively retrieve tickets from the past that are in line with a current request based on case-based reasoning or natural language processing, knowledge representation and ontology modeling approach	**I:** (Graef et al. 2020; Potharaju et al. 2013)
Note: I = instantiation; **C** = concept				

To exploit these potential benefits, we restructured the IT support process (as-is situation) to define a hybrid task division based on the functionalities of AI. Thereby, detrimental effects of work-related issues on service employees' time and cognitive capacities can be reduced and the execution of problem-solving activities can be substituted or augmented (see Figure 3, dashed areas). The process specifies the substitution of initial contact with support seekers by an AI-enabled agent that *locates* and sends a solution. A well-documented request is handed over to 1st level employees if the AI could not resolve it. For continued processing, embedded AI augments employees by *locating* suitable solutions for a respective request. If solutions are not applicable, the AI checks documentation for completeness and suggests a 2nd level unit to augment the *escalation* of requests. In the 2nd level, solutions from a specialized knowledge data base are suggested based on the content of the request to augment the *adaptation* and *generation* of solutions by employees.

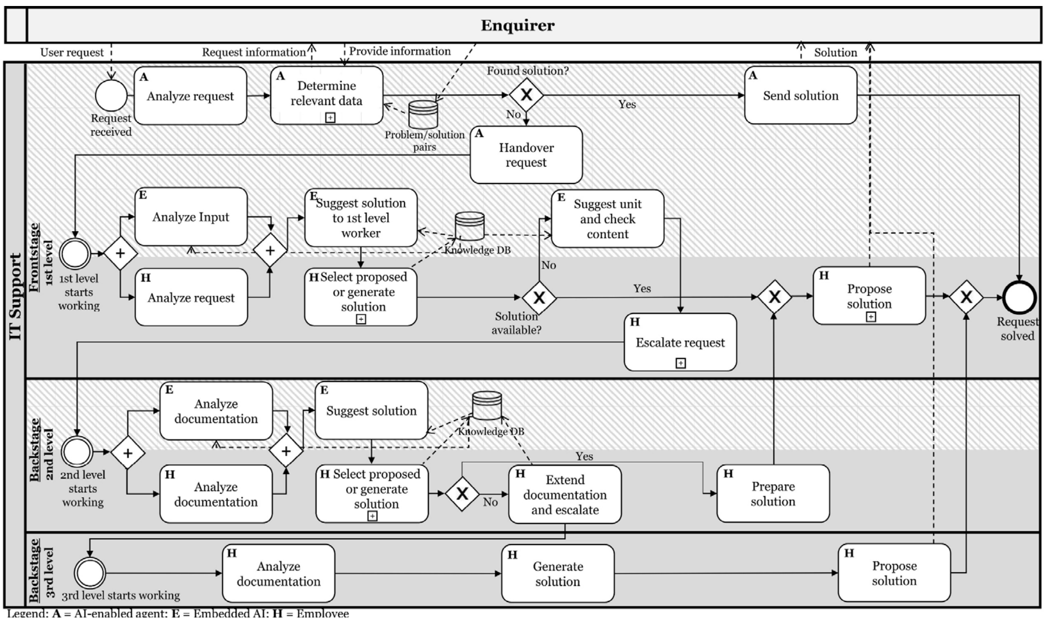

Figure 3. To-be Solution

9.5 Evaluation

Both developed IT support process models (as-is situation and to-be solution) were assessed using expert interviews (see Research Approach).

As-is situation: Experts' comprehensive and validating feedback on the as-is situation showed that the process model covers the essential components (EI1,3) and "fully captures the processing activities and flow" (EI2). The identified work-related issues appropriately describe employees' challenges (EI1) and confirm experts' work experiences (EI2,3). "The linkage of problems certainly is observable" (EI1) and "issues are connected across hierarchy levels" (EI3). In this regard, experts considered the issues (1-4) in the 1st level to be serious, as they initiate subsequent problems in the process chain. Therefore, the experts emphasized the need for a working environment that considers the dependencies of issues (EI3) and "a continuous transfer of knowledge from the backstage to frontstage – as feedback loop" (EI1) to close knowledge gaps.

To-be solution: Experts expressed that the proposed AI solutions are highly suitable and have potential to reduce the identified process- and activity-related issues. Concerning the effects of presented AI solutions, experts expected effective workload relief (EI3) especially due to the "great potential of simple, recurring requests" (EI1) in the 1st level that can be automatized with a CA. The deployment of AI in the 1st and 2nd level was regarded to facilitate error-reduced processing of requests, "cause cognitive relief" (EI2), and promote service employees' performance with lower levels of experience (EI1,3). For the 2nd level, AI was acknowledged to speed up processing by reducing the likelihood of preceding issues and effectively supporting relevant activities, such as solution search (EI3). The demonstrated integration of AI was regarded as both necessary and process-compliant (EI1,3) and created interest in deploying these solutions (EI1). However, AI deployment should not eliminate the telephone channel, as personal contact remains important. To avoid support seekers' frustration, the CA should be able to efficiently record relevant information with an appropriate subset of questions if it fails to resolve a request. Lastly, the experts remarked that it is essential to ensure support seekers' and service employees' acceptance of these AI solutions (EI1,2.3). With reference to the process model, a clearer distinction of databases was proposed to improve the understandability (EI1).

9.6 Discussion

Seeking to increase the efficiency and cost-effectiveness of service delivery, companies increasingly adopt AI in technical support work contexts such as IT support. As knowledge on integrating human and AI in work processes to elevate performance is still scarce (Lu et al. 2020; Makarius et al. 2020), this paper proposes a socio-technical perspective to capture and redesign the IT support process and address the needs of service employees

(Alter 2020). By developing a hybrid task division between service employees and AI, identified work-related issues are addressed to improve work conditions for time-critical service delivery in lower hierarchy levels. According to DSR, we contribute knowledge by defining and describing the problem space with comprehensive insights about current IT support processes and related problem scenarios in the addressed application domain (Hevner et al. 2004; Vom Brocke et al. 2020). In addition, the results of this paper lay the foundation to proceed the development of relevance-motivated, innovative solutions by indicating which solutions might be suitable and relevant.

Based on the qualitative study, we could identify and evaluate bottom-up insights that refer to problem dimensions in the existing work organization of IT support. The adoption of a holistic process view showed that work-related issues are predominantly interdependent across support levels. This implies that the low quality of requests and problem-solving descriptions induces difficulties in the processing chain across hierarchy levels (see Figure 4, “as-is”). More specifically, insufficient descriptions by support seekers lead to incomplete documentation of requests in the 1st level. As a result, 2nd level employees have difficulty analyzing and understanding the problems as well as excluding steps toward a solution that have already been applied by 1st level employees. Furthermore, service employees face the problem of finding existing solution knowledge. Thus, large amounts of simple, recurring requests in the 1st level are escalated too frequently despite existing, but untraceable knowledge, causing an increase of workload in backstage divisions. In combination, these work-related issues cause additional, repetitive activities that slow down the service process and overstrain service employees’ time and cognitive resources. Taken together, the as-is situation emphasizes that an isolated consideration of problematic service process stages is of limited use to improve the work organization with AI. These dependencies of tasks and associated issues identified in this paper, inhibit an overall improvement of service work if merely one issue is addressed and solved with a specific AI solution in isolation. Thus, the design of a holistic socio-technical solution is required that ensures satisfactory outcomes for support seekers, while seeking to optimize the integration of the technical and social systems (Alter 2013). Therefore, we propose a purposeful reorganization of the IT support process (to-be solution) by integrating state-of-the-art AI technology across interconnected process stages. Thereby, the process is streamlined and the volume of processed requests and repetitive activities can be reduced (see Figure 4, “to-be”). In addition, the substitution and augmentation of (sub-)tasks with AI solutions might alleviate the impact of the six work-related issues. More precisely, substituting 1st level service employees’ handling of simple and recurring requests with AI-enabled agents in the form of CAs can decrease their workload. In addition, embedded AI might reduce cognitive load of 1st and 2nd level employees by augmenting them with displayed knowledge items that match a request. Furthermore, 1st level employees could be augmented with the proposition of suitable units and criteria-based content screening of documentation texts prior to escalation. The evaluation of the proposed to-be solution has shown that purpose and functionalities of AI solutions from previous research are applicable. However, the maturity of identified solutions varies, indicating the nascent state of research in this field. Therefore, we considered full technological artifacts, technical components, or concepts for the creation of the to-be solution. Developments for deploying AI in the 1st level, appearing as AI-enabled agents, are advanced. CAs are currently capable of answering FAQs autonomously as well as performing problem-solving activities for a limited proportion of error-related requests (e.g., retrieving emails from quarantine). However, for a purposeful substitution of tasks that strengthens a hybrid division of tasks in the 1st level, the linkage of AI and employees is lacking, e.g., the documentation and dispatchment of requests in cases of AI failure. Embedded AI applications that reliably retrieve knowledge based on textual input are technically feasible but have been scarcely realized in the IT support context. This knowledge retrieval functionality has the potential to augment support employees but lacks adaptation to the different working conditions in the 1st and 2nd level (e.g., speed of request processing, required level of detail). In addition, a solution is needed for 1st level support employees that combines proactive knowledge retrieval and support for the documentation and dispatchment (escalation) of requests. Generally, previous research on AI solutions is limited and mainly positioned in the field of computer science. Accordingly, publications have focused on the technical development of artifacts and the measurement of their efficiency with a restricted consideration for users' perspectives.

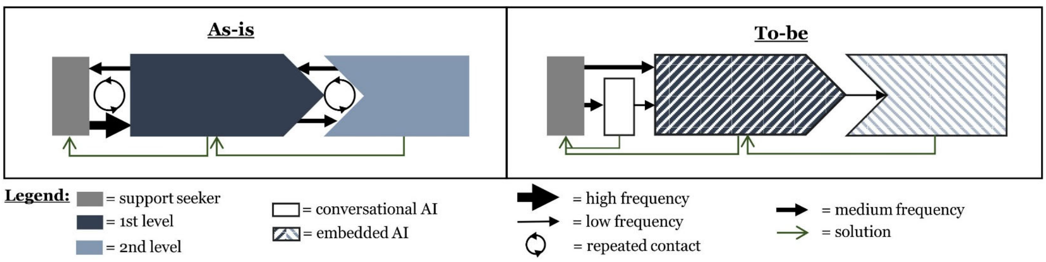

Figure 4. Interconnectedness and Resolution of Issues

Our results provide manifold contributions to research and practice alike. With regard to research, they complement emerging approaches that emphasize the significance of deliberately combining AI and employees in work settings (Alter 2020; Makarius et al. 2020). The paper promotes a socio-technical perspective as a suitable method to ensure a holistic perspective on AI adoption in service delivery contexts. In addition, this research contributes to investigations concerning technical support work and its, hitherto, under-researched sub-class IT support. The applicability of typical problem-solving activities (locate, adapt, generate, escalate) according to Das (2003) could be observed for IT support. Therefore, this theory constitutes a suitable starting point for future research to analyze and integrate AI and human activities in IT support. Furthermore, we provide a real-world process for IT support with located common work-related issues. Scholars can ground their research projects as relevance-motivated (Vom Brocke et al. 2020) on these insights and the proposed to-be process. Moreover, we present state-of-the-art AI solutions in scientific literature to support problem-solving activities in IT support (Krogh 2018). These contributions pave the way for future research, as current AI solutions do not fully address the interlocking of human and AI activities across process steps to enable hybrid IT service delivery. Further design-oriented research on AI solutions with suitable appearance (AI-enabled agent vs. embedded AI) should be initiated. Relevant research topics are the investigation of structured co-creation processes between AI-enabled agents and support seekers as well as AI-initiated handovers to 1st level service employees. Furthermore, criteria for suitable proactive knowledge suggestions through embedded AI should be identified for the different support levels to investigate employees' perceived level of support by AI. Accordingly, future studies should focus on interaction design with respect to information presentation and its impact on relevant factors such as trust, acceptance, and decision-making behavior. To ensure meaningful results, developed AI solutions should be evaluated in terms of their feasibility, suitability, ease of use, and impact on users in artificial as well as naturalistic settings. In addition to these design-oriented studies, future research should investigate the relationship between the effort required to develop, introduce, and maintain AI solutions in IT support and their benefits in the form of a more efficient service delivery process in terms of time savings, cost savings, and resolution of work-related issues (Jöhnk et al. 2021; Lewandowski et al. 2021).

For practice, the results also generate ample implications. The paper provides an approach to identify value-creating potential for AI deployment in IT support. In addition, the presented bottom-up insights assist companies in conducting focused analyses of their own processes to assess, whether these or similar problem dimensions exist that impede service delivery. The proposed process model with AI integration (to-be solution) can facilitate organizations' initiatives to improve their service delivery by deploying solutions that are tailored to individual conditions.

9.7 Conclusion

This paper addresses the potential of hybrid service delivery for technical support work, exemplified with IT support. More specifically, it considers the efficient management of service employees' time and cognitive resources by integrating suitable AI solutions in a redesigned IT support process. For this purpose, a socio-technical approach was adopted, which revealed the relevance of an overarching solution across tasks, process stages and hierarchical levels. We present a hybrid work process that introduces the substitution and augmentation of human tasks to address identified work-related issues and improve service delivery. Despite the valuable insights, the results of the paper are subject to a few limitations. The empirical data is based on a restricted number of expert interviews with a focus on technology-mediated support in the lower levels of the IT support hierarchy which limits the generalizability of findings. The assessment of additional experts or different forms of technical support (e.g., physical help desk) might yield additional or other work-related issues. Furthermore, the created to-be solution is based on the current state of knowledge and reported AI solutions in the knowledge base. The presented use cases are limited to published manuscripts and do not include commercial AI artifacts. Nevertheless, the results can be considered as a fruitful, guiding first step toward the exploration and design of AI-integrated technical support work. In addition, the findings could be applied in related service domains (e.g., customer service) to guide the redesign of service processes by integrating AI and human work.

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10 Integration of AI into Customer Service: A Taxonomy to Inform Design Decisions

Poser, M., Wiethof, C., & Bittner, E. A. C. (2022). Integration of AI into Customer Service: A Taxonomy to Inform Design Decisions. In *30th European Conference on Information Systems (ECIS),* Timișoara, Romania.

Abstract

Artificial Intelligence (AI) is increasingly deployed in customer service for various service delivery tasks. Research and practice alike have extensively dealt with the use, benefits, and effects of AI solutions in customer service contexts. Nevertheless, knowledge on AI integration is dispersed and unsystematized. This paper addresses this gap by presenting a taxonomy to inform design decisions for the integration of AI into customer service with five meta-dimensions, 12 dimensions, and 32 characteristics. Through a rigorous and systematic development process comprising multiple iterations and evaluation episodes, state-of-the-art AI solutions from practice and the current state of knowledge from research were systematized to classify AI use cases. Thus, we contribute with systemized design knowledge to, both, the theoretical knowledge base as well as to practice for application. Eventually, we disclose future research avenues addressing certain meta-dimensions as well as the extension of the taxonomy itself.

Keywords: Artificial Intelligence, Customer Service, AI Integration

10.1 Introduction

Customer service is currently undergoing a radical transformation driven by the integration of machine learning (ML), natural language processing (NLP), and related technologies, which are often subsumed under the term artificial intelligence (AI). In line with Gartner's prediction that 15 % of customer service interactions will be handled through AI by 2021 (Gartner, 2019), the successive application of AI is currently revolutionizing customer service toward the service encounter 2.0 (Larivière et al., 2017). Due to their advancing capabilities to autonomously handle inquiries, AI-enabled technologies, such as conversational agents (CAs), are implemented in various business contexts (e.g., finance, e-commerce, IT support) to elevate the efficiency and cost-effectiveness of text-based service delivery (Dwivedi et al., 2021; Gartner, 2019; Sarker, 2021; Xu et al., 2020). Thereby, organizations are able to enhance the availability and accessibility of their service provision as well as to reduce service employees' (SEs) workload, who can focus on more complex requests. Accordingly, AI progressively substitutes tasks of frontstage SEs, such as responding to customers' requests (Huang and Rust, 2018; Davenport et al., 2020). Related research, inter alia, involves the advancement of autonomous service delivery by focusing on customers' experience with AI addressing the representation and behavior of CAs, e.g., assigning social cues and ensuring competence levels (Gnewuch et al., 2017; Adam et al., 2020).

However, despite technological advancements, AI is still far away from fully substituting human intelligence beyond narrow domains (Dellermann et al., 2019). This means that AI can so far reliably handle simple requests for which unique relationships between the problem and solution have been established through training. For more complex requests with a distinct problem but multiple solutions, AI still regularly provides unsuitable answers (Krogh, 2018; Levy, 2018). Therefore, AI and human intelligence should be combined to allow SEs and AI to work side-by-side and foster their collaborative interplay (Wilson and Daugherty, 2018; Wirtz et al., 2018). In this vein, AI-based customer service solutions can support organizational service delivery by displaying answers to SEs to facilitate their inquiry processing. Additionally, AI can recognize intentions and emotions of the inquirer via natural language understanding leading to improved value co-creation during customer-SE interaction (Canhoto and Clear, 2020; Bassano et al., 2020; Sujata et al., 2019). Moreover, SEs can complement AI in various ways, e.g., through training, explaining, and sustaining (Keyser et al., 2019; Dellermann et al., 2019).

To realize efficient service delivery involving SEs and AI, a systematic orchestration of their capabilities and weaknesses is required (Paluch and Wirtz, 2020). Hence, the adoption of AI in customer service demands the differentiation between the roles of SEs and AI and the determination of the interaction with each other and the customer (Larivière et al., 2017; Robinson et al., 2020). Despite the increased interest in research and practice to deploy ML-based AI technology for online customer service, insights on how to integrate it into organizations are scarce (Benbya et al., 2021). Related to this, there is a lack of knowledge in research regarding the interrelationships between SE, customer, and AI within a socio-technical system of an organization's customer service (Bock et al., 2020). This includes the embedding in organizational work and process structures as well as the forms of interaction between SE, customer, and AI (Bock et al., 2020; Keyser et al., 2019). To address these knowledge gaps and provide systemized knowledge about the integration of AI for text-based customer service, the following research question is addressed: *How can conceptual and empirical knowledge on the integration of AI in customer service be classified to provide design decision guidance?*

We develop a taxonomy to inform design decisions by adopting the perspective of a single AI use case, which is analyzed or planned for implementation. Thereby, we aim to contribute to, both, the theoretical knowledge base as well as to practice for application with systemized knowledge from research and commercial solutions. Regarding theory, we provide relevant characteristics to be considered when investigating AI in different stages of the customer service process. Considering practical and managerial implications for IT management and development, businesses can advance their existing customer service delivery or implement novel interaction types aligned to the dimensions and characteristics of the taxonomy. To address the research question, the paper is structured as follows: First, we give an overview of related work about customer service and AI. After that, we introduce our research approach including the taxonomy development process. We then present an evaluation of our taxonomy prior to completion followed by the description of the final taxonomy organized and aligned to each meta-dimension. Next, we report on the ex-post evaluation of our taxonomy. We close the paper with a discussion and conclusion.

10.2 Related Work: Customer Service and AI

Service represents an elementary category of industrialized economies and is defined as the "application of competences (knowledge and skills) by one entity for the benefit of another" (Sampson and Froehle, 2006; Maglio and Spohrer, 2008; Vargo et al., 2008, p. 145). A relevant field of service represents companies' customer service offerings in various industries, which typically refer to intangible service delivery directed toward people (e.g., consultancy) or objects (e.g., post-sales service for primary products) (Wirtz et al., 2018). To fulfill customers' needs and demands, this form of service delivery is prevailingly characterized by knowledge intensity and customization, which requires active participation of and input by customers during service provision (Maglio and Spohrer, 2008). As companies strive to deliver high quality service to satisfy customers, a complex set of service processes needs to be orchestrated that spans the complementary service environments frontstage (external) and backstage (internal) (Sampson and Froehle, 2006). In the frontstage, service encounters with customers take place to co-create service. The backstage covers processes that do not directly involve customers and are therefore invisible to them (Glushko and Tabas, 2008; Bock et al., 2020).

To increase service quality and customer satisfaction, research has focused on factors that increase the efficiency and effectiveness in these service environments (Brady et al., 2002; Bitner et al., 2000). In this context, investigations emerged that, inter alia, examine the utilization of technology to create innovative ways of providing, accessing, and manipulating information in the front- and backstage (Amorim et al., 2019). Accordingly, the accessibility and availability of service have been addressed with technology-based self-service concepts such as knowledge portals on websites (e.g., Scherer et al., 2015; Meuter et al., 2000). Furthermore, access to and reuse of knowledge in accordance with customers' inquiries has been improved for SEs, e.g., with repositories (Kankanhalli et al., 2011). In this way, research has accounted for the time-critical, complex, and knowledge-dependent nature of service delivery in customer service contexts (Froehle and Roth, 2004). As an extension of these technology-focused research efforts, recent endeavors focus on the role of AI in customer service (Bock et al., 2020). With its capacity to process and learn based on data, AI is capable of inferring solutions to problems, decision options, or executing actions (Campbell et al., 2020; Raj and Seamans, 2019; Davenport et al., 2020). Hence, the utilization of current narrow AI that bases on ML algorithms is considered to revolutionize service delivery by efficiently and cost-effectively automating service encounters and tasks (Huang and Rust, 2018; Østerlund et al., 2021). This transforms information-rich online customer service since AI is capable of partially substituting or augmenting service activities. To account for this, Ostrom et al. (2019) and Keyser et al. (2019) introduced infusion archetypes for frontstage service delivery involving the entities AI, customer, and SE: AI either *substitutes* SEs by autonomously performing customer encounters or *augments* SEs by supporting them invisibly or visibly to customers through providing relevant information synchronous to the customer interaction. In these settings, customers and SEs encounter AI in the form of an AI-enabled agent and/or embedded AI. The former is a virtually represented agent that facilitates human-like interaction via natural language (e.g., CA), whereas the latter is integrated into platforms or applications without virtual identity (e.g., ticket tool) (Glikson and Woolley, 2020). AI-enabled agents, such as CAs, have been predominantly developed and investigated to substitute mechanical and analytical tasks that require rule-based, systematic, and consistent processing involving data and information (Huang and Rust, 2018; Janssen et al., 2020). Therefore, CA designs focus on interaction and technical capabilities to process customers' inquiries by answering questions or solving problems (Gnewuch et al., 2017; Følstad and Skjuve, 2019; Luger and Sellen, 2016). For the backstage, embedded AI is capable of delivering insights about past inquiries and/or historical customer data to support SEs (Graef et al., 2020; Cheung et al., 2003). Complementing these studies, initial research considers the interconnection of front- and backstage processes and tasks with seamless handovers from CAs to SEs to avoid failure in AI-performed service encounters (Wintersberger et al., 2020; Poser et al., 2021).

The overall focus of these previous studies predominantly lies on the development of stand-alone solutions for AI-performed service encounters in the frontstage. In addition, so far, there is limited knowledge about the role, activities, and integration of AI in the backstage. In principle, systematic knowledge with a holistic perspective on the integration of AI into customer service covering front- and backstage is until now scarce (Bock et al., 2020).

10.3 Research Approach

This paper aims to shed light on relevant design decisions for the integration of AI into the front- and/or backstage of customer service contexts by identifying and systematizing integration characteristics. For this purpose, dimensions related to service processes and the interaction between AI and humans (SEs and customers) are explored. As this still represents a nascent phenomenon, for which existing knowledge has not yet been structured and organized, a classification of associated concepts can help to consolidate understanding and further sense-making in this complex domain. For this endeavor, taxonomies are a suitable method, as they ascertainably present relationships, commonalities, and differences of concepts (Kundisch et al., 2021; Nickerson et al., 2013; Bailey, 1994). Following Kundisch et al. (2021), we rely on the Design Science Research (DSR) paradigm by adopting a build-evaluate pattern to construct and assess our taxonomy (Hevner et al., 2004; Sonnenberg and vom Brocke, 2012). Accordingly, our research approach comprises two consecutive process phases: (1) development and (2) evaluation (see Figure 1).

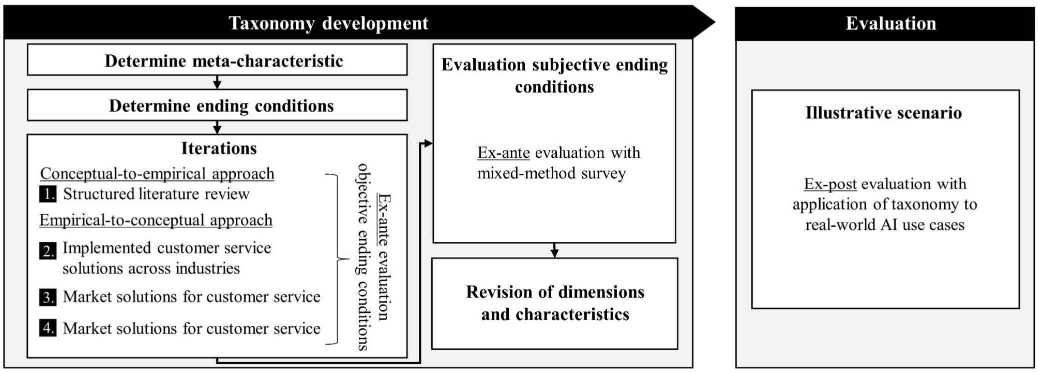

Figure 1. Research phases

For the development phase, the rigorous and systematic method of Nickerson et al. (Nickerson et al., 2013) is adopted. In line with DSR, the development and evaluation phases include several evaluation episodes (Venable et al., 2016; Kundisch et al., 2021). During development, formative ex-ante evaluations are performed. On the one hand, the research team assessed objective ending conditions for each development iteration (see Section 4.1). On the other hand, experts from research and practice conducted an evaluation of the subjective ending conditions with a complete version of the taxonomy (see Section 4.2). As part of the summative ex-post evaluation, the adapted, final taxonomy was applied to illustrative scenarios to provide insights on its usability and validity (see Section 6). Thereby, the taxonomy represents a DSR artifact of the type model (Kundisch et al., 2021), providing prescriptive knowledge on how to design (theory for design and action) the integration of AI into customer service from a socio-technical perspective (Gregor and Hevner, 2013; Gregor, 2006).

10.4 Taxonomy Development

The iterative taxonomy building method according to Nickerson et al. (2013) comprises several steps. The development process starts with the definition of the meta-characteristic to determine the purpose of the taxonomy (Nickerson et al., 2013; Lösser et al., 2019). We define the meta-characteristic as *design decisions for the integration of AI in service delivery processes for customer service* to facilitate researchers and practitioners in their analyses and design undertakings. In this context, design decisions refer to characteristics of service processes, the AI-based technology, and the interaction between humans and AI. The second step includes the definition of ending conditions to determine the requirements to conclude the development process. For the taxonomy development phase, we adopted the objective conditions proposed by Nickerson et al. (2013). In the third step, either an inductive (empirical-to-conceptual) or deductive (conceptual-to-empirical) approach is chosen to initiate the identification of characteristics and dimensions. The application of these approaches can alternate for subsequent iterations. For the conceptual-to-empirical approach, the focus lies on deducing and grouping characteristics into dimensions based on existing scientific knowledge. The empirical-to-conceptual approach involves the utilization of a variety of real-world objects to identify and classify characteristics into dimensions (Nickerson et al., 2013; Lösser et al., 2019). To initiate the development process, we chose the conceptual-to-empirical approach because initial scientific knowledge exists, but is so far unstructured. After each iteration, the assessment of the objective ending conditions by two taxonomy designers was analyzed in terms of their agreement to decide about the continuation of the development. In the following, we describe the four conducted iterations and depict the taxonomy evolution process in Figure 2.

10.4.1 Taxonomy building process

Iteration 1: For the first iteration, we adopted the conceptual-to-empirical approach to develop a profound understanding of the domain under study. To identify extant and pertinent scientific knowledge in various fields such as service science, human-computer-interaction, and information systems (IS), we conducted a systematic literature review following the guiding principles of Webster and Watson (2002) as well as vom Brocke et al. (2015). For the search process, we chose three domain-relevant IS databases, namely ACM Digital Library, AIS eLibrary, and ScienceDirect, to identify relevant peer-reviewed English publications. The search process was performed with a search string. By executing an initial database search, we identified suitable keywords. Based on these results, we created the following search string: *((“employee*” OR “customer*” OR “user*”) AND (“AI” OR “artificial intelligence”) AND (“service” OR “support”))*. The search delivered 738 hits across databases. In two subsequent screening phases, the fit of the publications to the defined meta-characteristic was independently assessed by two researchers. In the first screening phase, the number of publications was reduced by excluding duplicates and inaccessible articles. Furthermore, we used abstracts, titles, and keywords to exclude publications that did not focus on the service domain. The application of these exclusion criteria yielded 101 publications. During the second screening phase, these publications were subject to an in-depth full-text analysis. 19 articles remained after excluding publications, which focus on (1) robotics (2) pure technological aspects without service application, and (3) business intelligence. To reveal higher-order characteristics and dimensions, these articles were iteratively coded. In an initial round, two researchers inductively created a set of master codes (service domain, involved entities, aspects of human-AI-interaction, and service processes) by independently coding the 19 publications and resolving discrepancies. Based on these codes, characteristics were generated and their labeling continuously harmonized in discussions. Subsequently, these characteristics were individually grouped into dimensions by the researchers. Through constant exchange, divergent assignments were cleared and labels for the dimensions were jointly derived. As a result, the following seven dimensions were added to the taxonomy in the first iteration:

service stages, *AI role*, *task type*, *knowledge and data insights*, *form of AI appearance*, *AI transparency to customers*, and *data and knowledge processing*.

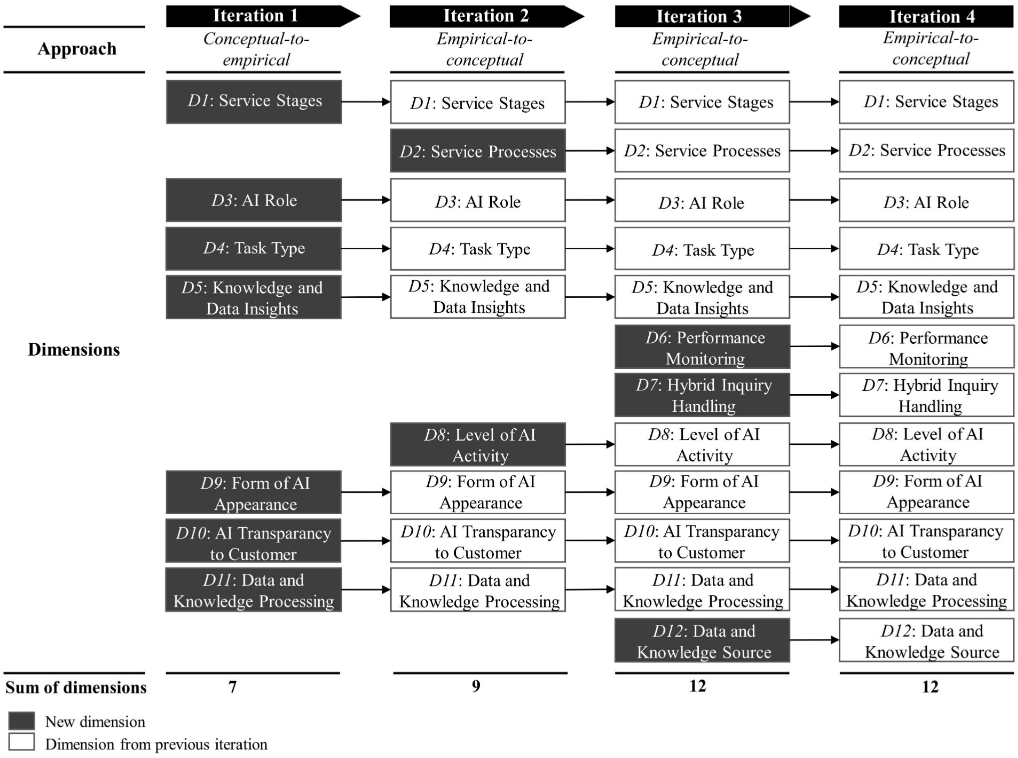

Figure 2. Taxonomy development process and evolution of dimensions

Iteration 2: Following the conceptual iteration, we chose the empirical-to-conceptual approach to complement the taxonomy with insights induced from real-world objects. The focus in the second iteration was on obtaining real-world data to sustain knowledge about the integration of AI into companies' service delivery processes. Following Short et al. (2002), we applied the stratified random sample method to acquire a representative sample of companies. In this way, a sample of companies can be subdivided into meaningful nonoverlapping groups to account for the diversity of industrial sectors. For the selection of international companies, we utilized the most recent Fortune 500 Global list (Fortune Media, 2019). With the objective of obtaining an appropriate sample size of 80 companies (Short et al., 2002), we selected four companies for each of the 20 industrial sectors, which are specified by Fortune Media. We conducted a systematic data collection process to examine companies' text-based and AI-enabled contact channels. To this end, companies' websites were visited and examined from a customer perspective to capture the types of text-based channels, characteristics of service interactions, and sequence of service processes via descriptions, process models, and screenshots. The subsequent qualitative analysis involved independent coding of documented case data by two researchers. With the help of the dimensions from the first iteration, we discovered that merely nine of 80 companies operating in seven sectors utilize AI for service encounters (see Appendix Table A1). Based on these insights, several characteristics were identified and merged into two additional dimensions for the taxonomy: *service processes* and *level of AI activity*.

Iteration 3: In the light of service stages with (frontstage) and without (backstage) direct customer contact, we examined 16 market solutions for AI-based customer service with AI-based customer service software. With reference to Gartner's Magic Quadrant (Gartner, 2020), in which vendors are evaluated based on their market positioning, leading, challenging, and visionary, solutions were selected and compared with entries from two suitable databases (capterra.com/customer-service-software, quicksprout.com/best-customer-service-software). For a structured data collection, we analyzed the websites of all vendors to document information in the form of reports, videos, and images. Qualitative analysis of these data, again conducted independently by two researchers, led to three additional dimensions: *performance monitoring*, *hybrid inquiry handling*, and *data and knowledge source*.

Iteration 4: The inclusion of additional dimensions in the preceding iteration required an additional empirical investigation. Therefore, similar to iteration three, a sample specifically focusing on conversational AI market solutions for the frontstage was produced. By using a practice-oriented evaluation from Forrester Research (Jacobs et al., 2019) and entries from two databases (g2.com/categories/conversational-intelligence, capterra.com/conversational-ai-platform-software), suitable solutions were identified. The resulting sample comprises 14 vendors, excluding duplicates from iteration three. The analysis of collected information via vendors' websites did not result in additional dimensions. Accordingly, in this iteration, the development phase was concluded as all objective ending conditions by Nickerson et al. (2013) were met. To prepare the evaluation of subjective ending conditions, we consolidated the taxonomy by inductively determining and ordering five meta-dimensions (*service context*, *capabilities*, *deliverables*, *integration*, and *intelligence*), which aggregately describe the content of the derived dimensions.

10.4.2 Ex-ante evaluation of subjective ending conditions

To ensure usefulness and applicability for research and practice, we assessed the content of the taxonomy with an ex-ante evaluation (Szopinski et al., 2019; Kundisch et al., 2021). Therefore, a mixed-method survey was utilized to collect quantitative and qualitative data from experts. To this end, our questionnaire included the taxonomy from iteration four with definitions for meta-dimensions, dimensions, characteristics, and questions covering the five subjective ending conditions (concise, robust, comprehensive, extendible, and explanatory) proposed by Nickerson et al. (2013). These ending conditions were each evaluated with a five-point Likert scale (from 1 (strongly disagree) to 5 (strongly agree)) and open-ended questions to receive extensive evaluation output and qualitative feedback for improvement. As the taxonomy is intended to guide researchers and practitioners alike in making design decisions to integrate AI into customer service, a heterogeneous group of experts from science (professor IS (ES1), research associates IS (ES2, ES4, ES5), associate professor IS (ES3)) and practice (machine learning engineer (EP1), senior architect (EP2), IS agent (EP3), software developer (EP4), software architect (EP5)) was recruited. For the selection, a purposive sampling strategy was chosen to obtain individuals who have (1) profound experience in taxonomy development and/or (2) knowledge about the role and deployment of AI in customer service.

By defining these selection criteria, relevant insights concerning content and formal aspects of the taxonomy could be derived. The analysis of the quantitative data delivered means and medians above 4.0 for the five subjective ending conditions: **concise** (M = 4.00; SD = 0.74; Mdn = 4), **robust** (M = 5.00; SD = 0.52; Mdn = 5), **comprehensive** (M = 4.00; SD = 0.52; Mdn = 4), **extendible** (M = 5.00; SD = 0.97; Mdn = 5) and **explanatory** (M = 4.00; SD = 0.52; Mdn = 4). These ratings at good to excellent level and the low dispersion of data illustrate the usefulness and applicability of the content and structure of the taxonomy. With respect to experts' qualitative comments, the analysis of data revealed recommendations for improvement that were implemented as follows. The label for the second dimension was changed from "Service Processes" to "Service Process Continuity" and the definition adapted (ES1). The definitions for the three characteristics of the third dimension were adjusted to clarify their focus (ES1, ES4). The description of the sixth dimension was extended to specify the meaning of the two characteristics. (ES4). The definitions for the tenth dimension and its two characteristics (ES1) and the characteristics of the eleventh dimension were refined (ES4, EP2, EP1). For the meta-dimension "Capabilities" the definition was refined (ES2), whereas the definition of the meta-dimension "Deliverables" was extended (ES2). These adjustments refer to refinements of content through adapting and extending definitions of meta-dimensions, dimensions, and characteristics. Thus, the objective ending conditions were still fulfilled.

10.5 Taxonomy of AI Integration into Customer Service

After four development iterations and content-related revisions initiated by the ex-ante evaluation, the final version of the taxonomy encompasses 12 dimensions, and 32 characteristics organized into five meta-dimensions (see Figure 3). Following Püschel et al. (2016), we classified the characteristics of each dimension as either mutually exclusive or non-exclusive to create a clearly structured and concise taxonomy. By establishing clear and delimited definitions, redundancy was counteracted to allow for the selection of a confined set of characteristics. To structure the taxonomy, we arranged the meta-dimensions in sequential order of their application for analysis and design to facilitate design decisions for the integration of AI for service delivery into customer service contexts. With *service context*, the application area of AI in customer service is determined. Subsequently, AI's *capabilities* are defined to determine the *deliverables* in the form of distinct outputs. By specifying the *integration* of AI, the interaction with customers and SEs, the appearance and behavior are defined. Concluding, the *intelligence* of AI is determined in accordance with the previous design decisions. In the following sub-sections, we present and describe the dimensions and characteristics for each of these meta-dimensions with justificatory references from research and practice (see Appendix Table A1 for practice references).

Service context: Based on the service context, the deployment of AI in customer service is determined in relation to *service stages* (D_1) and the nature of *service process continuity* (D_2). With respect to ***service stages***, AI can be utilized in the *frontstage* (D_1,C_1) to handle inquiries in direct contact with customers (Robinson et al., 2020; Fingerle et al., 2002). The application of AI in the *backstage* (D_1,C_2) involves processing of inquiries without direct customer contact (Zhang et al., 2020; Campbell et al., 2020). Associated with the deployment of AI in service stages is the determination of the type of ***service process continuity***, which refers to the temporal alignment of AI-integrated service delivery processes. *Disconnected* (D_2,C_1) processes imply unconnected inquiry processing steps between service stages involving SEs and AI with time lags and/or contact channel switches (I2U, I2W, I2WD). A *connected* (D_2,C_2) process continuity represents a direct connection between the service stages for request processing steps involving SEs and AI (I2N, I2AD, I2C, I2AM, I2AT, I2H).

<table>
<tr><th>MD</th><th colspan="2">Dimensions</th><th colspan="4">Characteristics</th></tr>
<tr><td rowspan="2">Service Context</td><td>D_1: Service Stages</td><td>NE</td><td colspan="2">Frontstage</td><td colspan="2">Backstage</td></tr>
<tr><td>D_2: Service Process Continuity</td><td>NE</td><td colspan="2">Disconnected</td><td colspan="2">Connected</td></tr>
<tr><td rowspan="2">Capabilities</td><td>D_3: AI Role</td><td>NE</td><td>Support</td><td colspan="2">Augmentation</td><td>Performance</td></tr>
<tr><td>D_4: Task Type</td><td>NE</td><td>Mechanical</td><td>Analytical</td><td>Intuitive</td><td>Empathetic</td></tr>
<tr><td rowspan="2">Deliverables</td><td>D_5: Knowledge and Data Insights</td><td>NE</td><td>Inquiry-related</td><td>Process-focused</td><td>Customer-related</td><td>Socio-emotional</td></tr>
<tr><td>D_6: Performance Monitoring</td><td>NE</td><td colspan="2">Human Agent Monitoring</td><td colspan="2">AI Monitoring</td></tr>
<tr><td rowspan="4">Integration</td><td>D_7: Hybrid Inquiry Handling</td><td>ME</td><td>Simultaneous</td><td>Consecutive - toward human</td><td>Consecutive - toward AI</td><td>Consecutive - alternating</td></tr>
<tr><td>D_8: Level of AI Activity</td><td>NE</td><td colspan="2">Reactive</td><td colspan="2">Proactive</td></tr>
<tr><td>D_9: Form of AI Appearance</td><td>ME</td><td colspan="2">AI-enabled agent</td><td colspan="2">Embedded AI</td></tr>
<tr><td>D_{10}: AI Transparency to Customers</td><td>ME</td><td colspan="2">Unknown</td><td colspan="2">Known</td></tr>
<tr><td rowspan="2">Intelligence</td><td>D_{11}: Data and Knowledge Processing</td><td>NE</td><td colspan="2">Machine Learning</td><td colspan="2">Rule-based Reasoning</td></tr>
<tr><td>D_{12}: Data and Knowledge Source</td><td>NE</td><td>Input before Interaction</td><td colspan="2">Input during Interaction</td><td>Input after Interaction</td></tr>
<tr><td colspan="7">Note: MD = meta-dimension; ME = mutually exclusive; NE = non-exclusive</td></tr>
</table>

Figure 3. Taxonomy of AI integration into customer service

Capabilities: The scope of application for AI in customer service is guided by its capabilities, which are subdivided into the dimensions *AI role* (D_3) and *task type* (D_4). Regarding the ***role AI*** plays in service delivery, a distinction can be made between support, augmentation, and performance. AI can provide *support* (D_3,C_1) to deliver service by executing and handing over results of (sub-)tasks (Canhoto and Clear, 2020; Ostrom et al., 2019; Keyser et al., 2019). By actively collaborating on a task with SEs, AI can *augment* (D_3,C_2) service delivery tasks (Xu et al., 2020; Amorim et al., 2019; Campbell et al., 2020; Ameen et al., 2021). Furthermore, AI can *perform* (D_3,C_3) (sub-)tasks autonomously (Canhoto and Clear, 2020; Macnish and Fernandez Inguanzo, 2019; Zhang et al., 2020; Göker and Roth-Berghofer, 1999). The utilization of AI capabilities also refers to different ***task types*** in customer service. When applied to *mechanical tasks* (D_4,C_1), AI can be used for standardizable, repetitive, routine, and transactional tasks that require consistency in execution (Canhoto and Clear, 2020; Huang and Rust, 2018). For tasks with an *analytical* (D_4,C_2) nature that require logical thinking and are executed based on data, information, and knowledge, AI can provide analytical functions (Huang and Rust, 2018; Canhoto and Clear, 2020). Furthermore, AI can be applied for *intuitive tasks* (D_4,C_3) that require experiential and context-based interaction and thinking. In addition, AI can be utilized for *empathetic tasks* (D_4,C_4) with a salient emotional and interactive character that requires empathy and emotional analytics (Canhoto and Clear, 2020; Huang and Rust, 2018).

Deliverables: In customer service, AI can produce two types of output as deliverables: *knowledge and data insights* (D_5) and *performance monitoring* (D_6). The ***knowledge and data*** AI can supply to customers and/or SEs relate to four different forms of insights. AI can provide knowledge and/or information that relate to the *content of an inquiry* (D_5,C_1) (Xu et al., 2020; Amorim et al., 2019). *Process-focused* (D_5,C_2) clues can be presented for service interactions (Canhoto and Clear, 2020; Amorim et al., 2019). Insights related to the customer can comprise *customer-related* (D_5,C_3) information (e.g., history of contact) (Libai et al., 2020; Campbell et al., 2020) or *socio-emotional* (D_5,C_4) insights related to customers' sentiments (Amorim et al., 2019; Canhoto and Clear, 2020). The ***performance monitoring*** for and with AI relates to *human agent monitoring* (D_6,C_1) or *AI monitoring* (D_6,C_2). The former provides insights on SEs' workload, inquiry volume, and trends (I3S, I3SN, I3M, I4AI, I3V, I3Z, I3S, I3CR). The latter refers to insights into AI's performance in terms of interaction behavior and the status of the knowledge base to identify potential for improvement (I4L, I4AV, I4IN, I3S, I4KO, I3V).

Integration: The representation and integration of AI into customer service encompass four dimensions: *hybrid inquiry handling* (D_7), *level of activity* (D_8), *form of appearance* (D_9), and *AI transparency to customers* (D_{10}). The ***hybrid inquiry handling*** determines the sequence, in which inquiries are handled by the SE and AI. On the one hand, the sequence can be *simultaneous* (D_7,C_1), i.e., the SE and AI are working together on an inquiry at the same time (I3SN, I3M, I3AP, I3F, I4EG, I3K, I4VS, I4O, I3P, I3SAP, I3Z, I4L, I4N, I4I, I4SF). On the other hand, the sequence can be *consecutive*, either *toward human* (D_7,C_2) or *toward AI* (D_7,C_3). Toward human, the AI handles the inquiry autonomously and forwards it to the SE once a determined condition is fulfilled, and vice versa toward AI (I3SN, I3Z, I3F, I4N, I4OA, I4IS, I4CO, I3E, I3C, I4IN, I4KO, I4L, I4VS, I4SF). A third alternative is a *consecutive-alternating* (D_7,C_4) sequence. In this case, the AI and SE handle the inquiry autonomously and hand it over to each other every time a determined condition is fulfilled (I4AI). The ***level of activity*** represents the activity behavior of the AI in interactions with SEs or customers. Either the AI is *reactive* (D_8,C_1) or *proactive* (D_8,C_2) in its behavior. When the AI is reactive, it is passive and interacts once it is triggered (I2U, I2C, I2N, I2AD, I2WD, I2W). When it is proactive, the AI is active and interacts of its own accord (I2AM). The ***form of AI appearance*** defines the form, in which AI appears in customer service. If the AI has an identity as agent with a virtual representation and interacts through natural language with SEs or customers, it is an *AI-enabled agent* (D_9,C_1) (Prentice and Nguyen, 2020; Xu et al., 2020; Campbell et al., 2020; Canhoto and Clear, 2020; Macnish and Fernandez Inguanzo, 2019; Svenningsson and Faraon, 2019; Gelbrich et al., 2020; Zhang et al., 2020). If it is integrated into platforms or applications in use and neither has an identity nor a visual representation, it represents an *embedded AI* (D_9,C_2) (Zhang et al., 2020; Chromik et al., 2020; Göker and Roth-Berghofer, 1999). The ***transparency of AI to customers*** refers to the degree, to which the presence of AI is apparent to customers. The customers are either not aware of AI's presence during service delivery, which makes it *unknown* (D_{10},C_1) (Canhoto and Clear, 2020; Aoki, 2021; Robinson et al., 2020), or they are aware of AI's presence, which makes it *known* (D_{10},C_2) (Canhoto and Clear, 2020; Robinson et al., 2020; Macnish and Fernandez Inguanzo, 2019; Svenningsson and Faraon, 2019; Aoki, 2021).

Intelligence: The intelligence of AI-integrated customer service is defined by the way it receives and handles data and knowledge for customer service tasks. With this, it covers two dimensions: *data and knowledge processing* (D_{11}) and *data and knowledge source* (D_{12}). The ***data and knowledge processing*** describes the underlying technology, which defines how AI processes information and knowledge. For one thing, AI can be trained and based on *Machine Learning* (D_{11},C_1) using learning algorithms for processing existing data toward pattern and entity recognition. This also covers the ability of AI to process and analyze natural language data to understand and generate natural language (Canhoto and Clear, 2020; Campbell et al., 2020). For another thing, AI can also be based on "if-then" pattern-matching rules through *rule-based reasoning* (D_{11},C_2) (Fingerle et al., 2002; Cheung et al., 2003; Göker and Roth-Berghofer, 1999). The ***data and knowledge source*** identifies the source from where the AI gets the data and knowledge. This data *input* can happen *before* (D_{12},C_1), *during* (D_{12},C_2), or *after* (D_{12},C_3) the *interaction*. First, the AI's knowledge base can be built by data and knowledge provided before the interaction (I4AV, I4CO). Then, the AI's knowledge base can continuously evolve through optimization based on and during the interaction (I4IS, I4AI, I4L, I4N, I4AI, I3P). And at last, AI's knowledge base can continuously evolve through implementing feedback and learnings after each interaction (I3E, I4KO, I4AV, I4IN, I4AI, I3F, I4CO).

10.6 Ex-Post Evaluation: Taxonomy Application

To adopt a rigorous evaluation strategy, we applied the framework by Szopinski et al. (2019) and chose the method 'illustrative scenario' to assess the coherence of the final taxonomy with the meta-characteristic. To this end, two real-world AI use cases were classified as objects with the taxonomy. To verify the validity of the taxonomy's purpose, on the one hand, a case was selected, where an AI-enabled agent in the form of a CA has already been implemented for service delivery in the frontstage (organization X). On the other hand, a case was chosen, in which the deployment of an embedded AI solution is planned to assist SEs in frontstage interactions (organization Y). To analyze the reliability of the taxonomy, two researchers and three practitioners utilized the taxonomy along the sequential order of meta-dimensions for design decisions. For organization X, the researchers and one practitioner with affiliation to the organization classified the existing AI use case. Two members from organization Y and the same researchers performed the classification for the planned AI use case in organization Y. The two researchers were enabled to classify the two use cases by a presentation of the core features derived from a qualitative data analysis based on eleven semi-structured interviews (organization X = five, organization Y = six) with business unit members, product owners, and documents about the IT architecture and modules. The results of the classification are presented in Table 1 by providing the rations of selected characteristics per dimension for each use case.

Table 1. Classification Results of AI Use Cases

<table>
<tr><th colspan="12">Hit ratios for characteristics (X ; Y)</th></tr>
<tr><td colspan="6">D_1,C_1: 100 % ; 0 %</td><td colspan="6">D_1,C_2: 0 % ; 100 %</td></tr>
<tr><td colspan="6">D_2,C_1: 100 % ; 0 %</td><td colspan="6">D_2,C_2: 0 % ; 100 %</td></tr>
<tr><td colspan="4">D_3,C_1: 100 % ; 75 %</td><td colspan="4">D_3,C_2: 0 % ; 100 %</td><td colspan="4">D_3,C_3: 67 % ; 0 %</td></tr>
<tr><td colspan="3">D_4,C_1: 100 % ; 25 %</td><td colspan="3">D_4,C_2: 0 % ; 75 %</td><td colspan="3">D_4,C_3: 0 % ; 0 %</td><td colspan="3">D_4, C_4: 0 % ; 0 %</td></tr>
<tr><td colspan="3">D_5,C_1: 100 % ; 75 %</td><td colspan="3">D_5,C_2: 100 % ; 100 %</td><td colspan="3">D_5,C_3: 33 % ; 25 %</td><td colspan="3">D_5,C_4: 0 % ; 0 %</td></tr>
<tr><td colspan="6">D_6,C_1: 100 % ; 0 %</td><td colspan="6">D_6,C_2: 100 % ; 100 %</td></tr>
<tr><td colspan="3">D_7,C_1: 0 % ; 75 %</td><td colspan="3">D_7,C_2: 100 % ; 0 %</td><td colspan="3">D_7,C_3: 0 % ; 0 %</td><td colspan="3">D_7,C_4: 0 % ; 25 %</td></tr>
<tr><td colspan="6">D_8,C_1: 67 % ; 75 %</td><td colspan="6">D_8,C_2: 33 % ; 25 %</td></tr>
<tr><td colspan="6">D_9,C_1: 100 % ; 75 %</td><td colspan="6">D_9,C_2: 0 % ; 25 %</td></tr>
<tr><td colspan="6">D_{10},C_1: 0 % ; 100 %</td><td colspan="6">D_{10},C_2: 100 % ; 0 %</td></tr>
<tr><td colspan="6">D_{11},C_1: 100 % ; 100 %</td><td colspan="6">D_{11},C_2: 100 % ; 0 %</td></tr>
<tr><td colspan="4">D_{12},C_1: 100 % ; 75 %</td><td colspan="4">D_{12},C_2: 0 % ; 75 %</td><td colspan="4">D_{12},C_3: 100 % ; 75 %</td></tr>
</table>

For the use case of organization X, the practitioner and researchers agreed on all characteristics in nine dimensions; for eleven dimensions, they agreed on at least one characteristic. For the use case of organization Y, the practitioners and researchers agreed on all characteristics for five dimensions; in seven dimensions they agreed on at least one characteristic. Only for five characteristics in four dimensions in use case Y, classifications did not match. However, it is difficult to achieve perfect interrater agreement for the whole taxonomy regarding the option to choose more than one characteristic in most dimensions. With this, the classification of the two specific use cases along the characteristics of the taxonomy reveals a good reliability and well-suited applicability of the taxonomy for practice. Moreover, the achieved characterization of the two use cases with reference to their attributes indicates a substantial validity of the taxonomy. After classifying their use cases, we also asked the practitioners for further feedback on different aspects related to the application of the taxonomy. First, the taxonomy appears understandable and clear. Especially for the planning scenario, it provided ideas and perspectives to the development, which need to be considered. Second, practitioners found it easy to use, i.e., they knew where and how it can be applied in their real-world scenario. At last, they argued for good feasibility and applicability of the taxonomy indicating the usefulness of our taxonomy. Based on these insights, we can confirm the coherence of the final taxonomy with the meta-characteristic to facilitate researchers and practitioners in their analysis and design undertakings concerning design decisions for the integration of AI in service delivery processes for customer service.

10.7 Discussion and Conclusion

With the developed taxonomy, we provide a first structured and elaborated overview of relevant design choices to integrate AI into the front- and/or backstage of customer service contexts. The compilation of characteristics across five meta-dimensions and 12 dimensions systematizes scattered knowledge from research and commercial applications in the still evolving research field of AI-enabled service. Thereby, two current research streams focusing on conceptual or technological aspects are integrated. Based on and complementing these insights with data from practice, we present an in-depth analysis of pertinent aspects of how AI can be integrated into customer service (Benbya et al., 2021). In addition, we answer the call for an investigation of the mutual interrelation between AI and the social as well as technical systems in service organizations (Bock et al., 2020). By adopting a holistic, socio-technical perspective for the development, the taxonomy reveals changes in connection to AI integration referring to service processes spanning front- and backstage, division of labor, and interaction between humans and AI. In particular, the taxonomy emphasizes that different constellations of the entities customer, SE, and AI emerge depending on the design decisions to integrate AI. As AI is not yet capable of solving all types of inquiries independently in the frontstage, the service process comprises sections where all entities interact simultaneously or handovers are initiated, introducing a change in interaction partners. Accordingly, depending on the AI use case, specific task- and process-related dependencies arise between AI and SE, which in turn impact the interaction with customers. Similarly, the integration of AI in the backstage has an impact on SEs, as working practices change through interaction with AI. Building on the current state of research and practice of AI and its deployment in customer service, our taxonomy enables the classification of use cases that are planned to be scientifically investigated or developed and/or planned for deployment in practice. By providing a sequential order of design decisions that are organized along the meta-dimensions, the selection of a confined set of characteristics regarding service context, capabilities, deliverables, integration, and intelligence of a specific AI use case is facilitated. In this respect, the results of the ex-post evaluation demonstrate a good handling of the taxonomy. Furthermore, a valid and reliable classification of AI use cases for customer service can be achieved by utilizing the taxonomy. These results underline the completeness, applicability, and effectiveness of the created taxonomy. Accordingly, our rigorously developed and evaluated taxonomy provides prescriptive design knowledge on how AI can be integrated into customer service to sustain the design and implementation process as well as the analysis of AI-based customer service applications (Kundisch et al., 2021; Gregor and Hevner, 2013).

The presented taxonomy provides many-faceted theoretical and practical contributions. Regarding research, we created, to the best of our knowledge, the first taxonomy that summarizes scientific insights and the status quo in practice on characteristics for the integration of AI in customer service. As a result, the structure for classification improves and fosters understanding in this research domain regarding characteristics for AI-infused customer service. Hence, these insights might encourage the extension and continuation of research for progressing AI-powered customer service solutions. Furthermore, it serves as a tool to systematically derive relevant and specific design decisions by incorporating various aspects that should be considered for the development of AI solutions. Moreover, we contribute insights on the integration of AI for, both, the external (frontstage) and internal (backstage) customer service environment (see Figure 4).

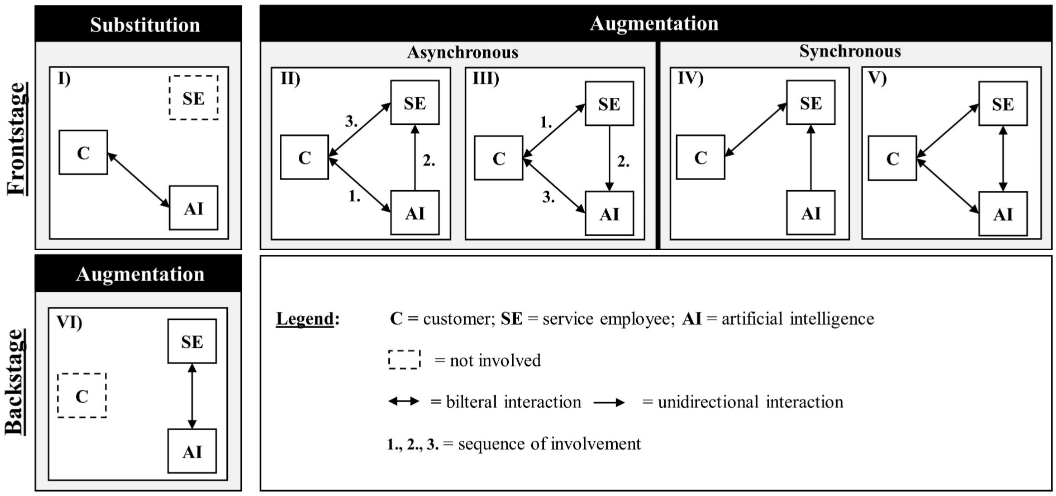

Figure 4. AI infusion archetypes covering front- and backstage

We validate existing infusion archetypes from Keyser et al. (2019) and Ostrom et al. (2019). More specifically, substitution (see Figure 4, I) and augmentation (see Figure 4, IV & V) of SEs by AI in frontstage service encounters could be confirmed. Furthermore, we identified additional infusion archetypes. In the frontstage, we introduce asynchronous augmentation (see Figure 4, II & III) where inquiries are handled consecutively with handovers from AI toward SEs or vice versa in cases a predetermined condition is fulfilled (e.g., imminent failure of AI). In addition, for the customer service backstage, we establish an infusion archetype of the type “augmentation” for the first time (see Figure 4, VI). For this archetype, the focus lies on AI use cases that facilitate service processes and tasks without direct customer contact, which are also of eminent relevance for service delivery. In this context, AI is deployed to augment SEs in processing inquiries by, inter alia, displaying suitable information that might facilitate decision-making.

In terms of practice, IT management and development can use the categorization to analyze deployed solutions to uncover gaps or plan implementation by determining characteristics of a specific use case. Therefore, the taxonomy provides a suitable blueprint to structure AI integration initiatives by classifying projects along the dimensions. Especially for planning AI integration, it adds more ideas and perspectives to be considered for the development. In fact, practitioners benefit from insights, which shed light on relevant AI-related characteristics, e.g., its role and task, which have been extensively developed by researchers. In addition, for integrating AI in their customer service processes, they can refer to state-of-the-art solutions we provide from practice. Eventually, the sequential order of our taxonomy can guide practitioners either through planning, executing, or analyzing AI integration for their specific use case.

Besides the promising contributions of this research, there are a few limitations to consider. First, our empirical data is based on a representative sample of solutions from practice. However, selecting and adding different or more solutions to our sample of empirical solutions could reveal and lead to different or more insights. Furthermore, even though we considered three domain-relevant IS databases, the results might vary when selecting different or more databases. This also applies to changes of our search string. Eventually, the selected samples of empirical cases and research contributions define and limit the taxonomy with its dimensions and characteristics. At last, regarding the reliability of our taxonomy, we could only consider two illustrative use case scenarios. To achieve and establish reliability, more practitioners may use and apply the taxonomy to their specific use cases. These limitations and obtained insights give rise to future research. In general, future work can build on our taxonomy, validate, or extend dimensions and characteristics. Considering our ex-post evaluation, we call for descriptive research to specifically enhance the applicability of the taxonomy and better showcase what design decisions must be made for the integration of an AI solution in customer service. Furthermore, different aspects can be addressed in more detail with respect to the individual meta-dimensions of the taxonomy. First, in terms of service context, the current state of knowledge indicates that AI solutions for backstage customer service are, so far, under-researched. In this context, research should focus on the development and design of AI solutions that promote hybrid service delivery without direct customer contact. Related to this, solutions should be developed that enable an AI-integrated, seamless, and efficient processing of inquiries across front- and backstage involving AI and SEs. Additionally, research should focus on mechanisms to establish acceptance toward AI and incentive systems for SEs and customers to utilize AI for service delivery. Lastly, approaches for learning scenarios are needed that allow for a continuous development of the competencies and knowledge base of the AI.

10.8 Appendix

Iteration 2			
Company	**URL**	**Company**	**URL**
Amazon (I2AM)	www.amazon.com/gp/help/customer/display.html?nodeId=508510&ref_=nav_cs_customerservice_2bf4fe8c5ec54e6bae2d1c24043f012b	United Parcel Service (I2U)	www.ups.com/us/en/help-support-center.page
China Mobile Communication (I2C)	eshop.hk.chinamobile.com/en/corporate_information/Customer_Service/index.html	AT&T (I2AT)	www.att.com/support/topic

Home Depot (I2H)	www.homedepot.com/c/customer_service	Walmart (I2W)	www.walmart.com/help
Walt Disney (I2WD)	help.shopdisney.com/hc/en-us	Adidas (I2AD)	www.adidas.com/us/help
Nike (I2N)	www.nike.com/us/help		
Iteration 3 *AI-based Customer Service Software*			
Salesforce (I3S)	www.salesforce.com/products/service-cloud/features	Pegasystems (I3P)	www.pega.com/products/platform/email-bot
Service Now (I3SN)	www.servicenow.com/content/dam/servicenow-assets/public/en-us/doc-type/resource-center/data-sheet/ds-customer-service-management.pdf	Microsoft (I3M)	dynamics.microsoft.com/de-de/customer-service/overview
Zendesk (I3Z)	support.zendesk.com/hc/en-us/articles/360057455393?_ga=2.178859299.64267010.1608134017-830973252.1608134017	Oracle (I4OA)	www.oracle.com/cx/service/b2c
SAP (I3SAP)	www.sap.com/products/service-cloud.html?btp=0106c0a9-f57d-429f-ab94-bd740a7f68e8	Freshworks (I3F)	freshdesk.com/freddy-ai-for-cx
Verint Systems (I3V)	www.verint.com/customer-engagement-cloud	Appian (I3AP)	appian.com/platform/overview.html
Creatio (I3C)	www.creatio.com/service	eGain (I3E)	www.egain.com/solutions/contact-centers
SugarCRM (I3S)	www.sugarcrm.com/de/solutions/sugar-serve	Kustomer (I3K)	www.kustomer.com/product/customer-service
Zoho (I3Z)	www.zoho.com/desk/zia.html	CRMNEXT (I3CR)	www.crmnext.com/crm/service
Iteration 4 *Conversational AI*			
LogMeIn (I4L)	www.bold360.com	Salesforce (I4SF)	www.salesforce.com/products/service-cloud/automated-customer-service
Nuance (I4N)	www.nuance.com/index.html	Verint Systems (I4VS)	www.verint.com/engagement/our-offerings/solutions/intelligent-self-service/virtual-assistant
Interactions (I4I)	www.interactions.com	eGain (I4EG)	www.egain.com/products/chatbot-virtual-assistant-software
Inbenta (I4IN)	www.inbenta.com/products/chatbot	Kore (I4KO)	kore.ai
Aivo (I4AI)	www.aivo.co	Cognigy (I4CO)	www.cognigy.com
Avaamo (I4AV)	avaamo.ai	IPSoft (I4IS)	amelia.com
247ai (I4AI)	www.247.ai	Omilia (I4O)	omilia.com

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11 Hybrid Teamwork: Consideration of Teamwork Concepts to Reach Naturalistic Interaction between Humans and Conversational Agents

Poser, M., & Bittner, E. A. C. (2020). Hybrid Teamwork: Consideration of Teamwork Concepts to Reach Naturalistic Interaction between Humans and Conversational Agents. In *15th International Conference on Wirtschaftsinformatik (WI)*, Potsdam, Germany.

Abstract

Hybrid teamwork between humans and conversational agents (CA) is a promising approach to augment humans' thinking and problem solving during task work. To realize a natural interaction, it is inevitable to consider research insights from human-centric disciplines for the design of CAs, as human team members have underlying assumptions regarding team work that need to be addressed to achieve valuable outcomes in hybrid teamwork settings. In this paper, we conducted a systematic literature review to consolidate past research on considered teamwork-specific psychological concepts for the design of CAs. The in-depth analysis of 19 publications demonstrates that, both, studies with a conceptual focus and CA instantiations, are primarily concerned with task-related teamwork concepts, while mostly disregarding relationship-related concepts. The results are discussed and implications for future research are identified.

Keywords: Hybrid teamwork, conversational agent, interaction design, team research, literature review.

11.1 Introduction

Incremental technological improvements in artificial intelligence (AI), machine learning (ML) and natural language processing (NLP) will in near future enable human-machine collaboration for diverse knowledge intensive work tasks [1, 2]. This hybrid teamwork is in line with the concept of intelligence augmentation (IA), which emphasizes a machine's facilitation of human thinking and problem solving [3]. Augmentation can help balance humans' bounded rationality in finding solutions, debias judgements, reduce noise in decision-making and foster creative task performance [4]. The realization of human-machine collaboration will encompass joint, interactive and dynamic task accomplishment through inter alia technology-generated advices (e.g. insights and predictions), which rely on vast amounts of data and thereby qualify as criteria for human workers' decision making [1]. Moreover, teamwork between humans and machines will entail and allow the delegation and allocation of (sub-)tasks to one another [5, 6].

Due to progressive NLP capacities, collaborative work in hybrid team settings could take place via natural language (written or spoken) [1]. In this vein, AI-powered conversational agents are a phenomenon that is increasingly addressed in scientific literature [7–9]. A CA is a software system, which is capable of autonomously interacting with humans via natural language [10]. In a hybrid team, which consists of a CA and at least one human member, the artificial entity could take over the roles of a facilitator, peer or expert [1, 7, 11]. As human collaboration for joint task work significantly depends on communication [12, 13] and the usage of natural language by artificial interlocutors enhances humans' expectations of a natural interaction with machines [14], the design of CAs should satisfy users' underlying assumptions for human teamwork. Therefore, to naturally and effectively collaborate with humans and comply with their tendency to anthropomorphize machines' behavior [15, 16], CAs require a cognitive model to, on the one hand, execute pre-defined team-relevant behaviors such as planning or goal specification. On the other hand, due to the dynamic nature of teamwork, CAs should be able to anticipate and flexibly react to changing subtasks with associated goals and human team members' intentions and actions [9, 17]. In addition, CAs need to behave in a transparent and predictable way and comply with human norms, while utilizing human communication principles [18–20].

The described progressive technological advancements can be exploited to reach naturalistic hybrid teamwork settings with CAs, but need to be complemented with knowledge on teamwork. Accordingly, the design of human-CA interaction should be guided by human-centered approaches [8, 9, 21–23]. It should be informed with findings from team research (cognitive psychology), which focuses on communication processes, action sequences in and psychological aspects of small groups, to strengthen CAs' capacity for teamwork and socialness in settings of shared task accomplishment [1, 7, 19, 24]. In order to make insights from teamwork research accessible and usable for the growing number of IS researchers designing CAs, a twofold objective is pursued in this paper. First, teamwork concepts that have so far been included in CA designs are systematized. Second, aspects of teamwork, which have been proven to be essential in team research are identified and presented. A systematic literature review is conducted to address the following research question: *Which teamwork-specific psychological concepts have so far been considered for the design of conversational agents for hybrid teamwork?*

The remainder of this paper is structured as follows: Section 2 covers the theoretical background and introduces established teamwork concepts. In section 3, the method of the systematic literature review is introduced. Subsequently, in section 4 the results of the review are presented and integrated. In Section 5, the findings are discussed and implications for future research are defined. Section 6 concludes with limitations of the study at hand and an outlook.

11.2 Theoretical Background

11.2.1 Teamwork Research

The essential principle of human teamwork is the integration of individuals' efforts to achieve a shared goal [11]. Accordingly, extensive research has focused on several team outcomes (e.g. effectiveness, productivity) to investigate teams' abilities to reach their objectives and accomplish tasks [25–27]. These team outcomes are particularly influenced by team processes and emergent states [26–28].

Team processes involve team members' interactions through verbal, behavioral and cognitive activities during task work [27, 29]. The investigations of teams' interactions have been led by the emergence of the fundamental theoretical framework by Marks et al. [29], as the concepts have been continuously verified [27, 30]. The authors developed a taxonomy of team processes with three different categories referring to different temporal phases and corresponding activities, which are defined in Table 1.

Table 1. Definition of activities for team processes [29]

Focus	*Cat.*	*Activities*	*Definition*
Task	Transition	Mission analysis & planning	Identify tasks, consider team resources and environmental conditions
		Goal specification	Identify and prioritize (sub-) goals
		Strategy formulation	Develop sequence of actions
	Action	Monitoring progress	Monitor task process and communicate status to team members
		Systems monitoring	Monitor team resources and environmental conditions
		Team monitoring & backup behavior	Support team members (1) with feedback, (2) through taking over activities or (3) through taking over a task
		Coordination	Coordinate time and sequence of interdependent actions
Relationship	Interpersonal	Conflict management	Prevent team conflicts by establishing conditions, resolve task and interpersonal conflicts
		Motivation & confidence building	Establish and maintain confidence, motivation and cohesion among team members
		Affect management	Manage emotions relevant for task execution (e.g. frustration)

Note. Category (Cat.).

Transition processes occur in the beginning of teamwork and include the steps of mission analysis, goal specification, strategy formulation and planning. Action processes refer to activities to accomplish team goals by coordinating actions, monitoring progress, systems and the team. Lastly, interpersonal processes span over each phase of teamwork and refer to conflict, affect and motivation management as well as confidence building. The transition and action processes are considered to be task-focused comprising behaviors directed at reaching joint goals (e.g. monitoring progress) [25, 27–29, 31]. The interpersonal processes are relationship-focused actions (e.g. encourage motivation) [25, 27, 29].

The concept of emergent states, introduced by Marks et al. [29], denotes teams' cognitive and affective states, which arise through and change in relation to team processes [26, 29, 30] (see Figure 1). Spanning almost two decades of research, various team level constructs have been investigated. In accordance to Mathieu et al. [27], a sample of the most intensively studied emergent state concepts in team research are presented in Table 2 with corresponding definitions [11, 30]. As with team processes, emergent states have also been distinguished into task- and relationship-related states [25]. Task-related states reflect how individuals' actions influence or provoke cognition and attitudes about task work (e.g. team confidence), whereas relationship-related states represent the team members' feelings about the nature of teamwork (e.g. trust) [27, 32].

Table 2. Definition of cognitive and affective emergent states

Focus	*Cat.*	*Emergent state*	*Definition*
Task	Cognitive	Shared mental models	Mental representations about the team task, resources, roles and responsibilities that are shared among team members [30, 33]
		Transactive memory systems	"Shared understanding of which member knows what as well as a structure that allows for storage, retrieval, and communication of that knowledge at the team-level" [30]
		Team Confidence	Comprises efficacy and potency beliefs and reflects teams' perception to accomplish a specific and a range of tasks across contexts [30, 34]
Relationship	Affective	Cohesion	"Shared attraction or bonding among team members that is grounded in social- or task-based aspects of team membership, and that drives team members to remain together" [30]
		Team trust	"Shared psychological state among team members comprising willingness to accept vulnerability based on positive expectations of a specific other or others" [35]
		Affective tone	"consistent or homogeneous affective reactions within a group" [36]
		Psychological safety	"A shared belief that the team is safe for interpersonal risk taking" [11]

Note. Category (Cat.).

As depicted in Figure 1, both, team processes and emergent states unfold over time during task work. The transition and action processes constitute crucial building blocks with varying time spans and depending on the task are repeatedly executed for subordinate tasks to accomplish the task.

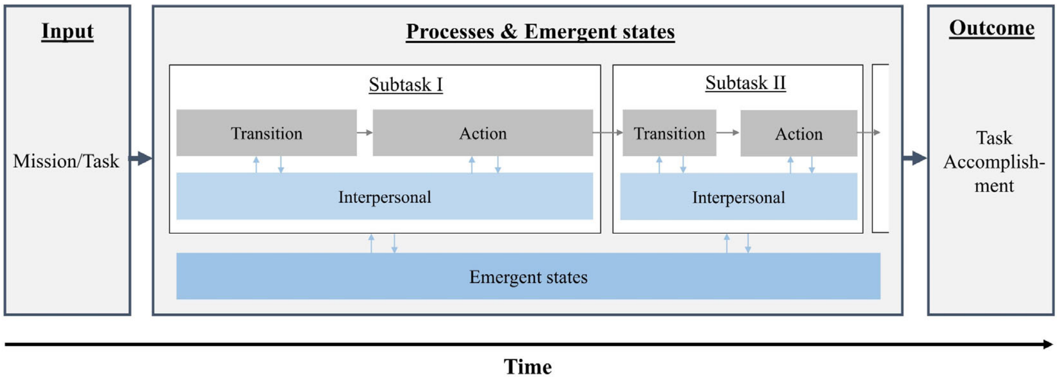

Figure 1. Temporal relationship of team processes and emergent states (adapt. [29])

Activities relating to interpersonal processes are performed to positively affect team functioning. In addition, emergent states evolve through task work and in turn have an impact on the different team-specific verbal, behavioral and cognitive activities.

11.2.2 Hybrid Teamwork with CAs

Following Seeber et al. and Bittner et al. [1, 7, 9], CAs are intelligent autonomous machines, which are capable of joining human teams. In accordance with the established work team definition by Kozlowski and Bell [11], we conceptualize these hybrid teams to comprise at least two members with one CA and at least one human member. So far, CAs can take over three roles in a hybrid team [7]: (1) a facilitator supports users' achievement of a task with directive behavior, (2) a peer makes contributions or challenges other members' comments and is a full member of the hybrid team, (3) an expert has a special expertise to supplement task work upon request.

To achieve natural interactions between humans and CAs for interdependent hybrid teamwork, a human-centric CA design should incorporate insights from human team research about factors, which enhance the effectiveness of teamwork. This application of transdisciplinary knowledge from cognitive psychology to design software-based systems is in line with the established "Computers as Social Actors" (CASA) paradigm. CASA bases on the social response theory, which proposes that individuals treat computers with social cues as social actors and apply social rules and norms of human-human interaction and associated expectations during human-computer-interaction [37, 38]. Multiple studies showed that humans mindlessly react to artificial entities with social cues (e.g. use of natural language, interactivity) by showing social reactions and behavior [14, 38, 39]. Consequently, due to the humanlike characteristics of CAs, individuals unintentionally apply social conventions, which are specific to the artificial interlocutors' cues and the social context. Hence, for effective hybrid teamwork, CAs need an understanding of fundamental sequences of task- and relationship-focused team processes and emergent states to affect the outcomes of shared tasks.

11.3 Research Method

A systematic literature review following the principles of vom Brocke et al. [40], Webster and Watson [41] and Cooper [42] was conducted to identify, assess and interpret existing research findings, which are relevant to answer the posed research question and derive implications for future research. The review process was structured along the five steps proposed by vom Brocke et al. [40].

In a first step, Cooper's taxonomy [42] was applied to determine the scope of the review. The focus was set on research outcomes, methods, applications and theories by integrating literature and identifying central issues to espouse a position. The conceptually organized literature addresses general scholars. In the second step, central definitions (Section 1) and key concepts were derived (Section 2).

To conduct the literature search process, in step three, domain relevant databases were selected: Web of Science, ScienceDirect, IEEE Xplore, ACM DL and EBSCO. For the construction of the search string, keywords, terms and synonyms for CAs and team work were identified by undertaking an initial search in the databases [43]. Subsequently, the literature search was conducted with the following search string: *(("conversational" OR "virtual" OR "digital") AND ("agent*" OR "assistant*") OR "chatbot*" OR "chatterbot*") AND ("team*" OR "team work" OR "hybrid team" OR "collabor*" OR "coop*"))*. The search string was applied to titles, keywords and abstracts and restricted to peer reviewed English literature. In total, the search process comprised two screening phases (see Table 3).

Table 3. Procedure of the literature search process

Database	*Search results*		*First screening*		*Second screening & Backward search*	
	n	*%*	*n*	*%*	*n*	*%*
Web of Science	235	29	27	29	6	35
IEEE Xplore	169	21	29	31	2	12
ACM DL	249	31	24	25	7	41
EBSCO	62	8	8	8	1	6
ScienceDirect	86	11	7	7	1	6
Total papers	**801**	**100**	**95**	**100**	**17(2)**	**100**

In the first phase, the search delivered 801 publications. By excluding irrelevant, unavailable literature and duplicates, 95 publications remained after reviewing titles and abstracts. Literature was excluded, if it had a focus on (1) robots (e.g. manufacturing machines), (2) pure technological characteristics of or approaches to develop CAs, (3) visual representations of CAs (e.g. gestures, eye gazing), (4) other forms of interaction than natural language (written or spoken), (5) communication specific prerequisites for CAs (e.g. repair acts, modality) or (6) knowledge and response training of CAs. In the second screening phase, publications for the in-depth analysis were selected by examining the full texts of the previously identified articles. 17 publications were identified by assigning them to three content-related categories: teamwork concepts, CA role and scope. The categories teamwork concepts and CA role were derived deductively. With regard to teamwork concepts, we differentiated between task- and relationship-focus of team processes and emergent states [25–27]. To determine whether publications deal with team processes or emergent states, behaviors and states from human teamwork literature were utilized (see Section 2.1) [26, 27, 29, 31]. By referring to the classification of Bittner et al. [7], the roles of CAs (peer, expert, facilitator) were assessed. The category scope was developed inductively by assessing whether the authors either focused on pure conceptual aspects or CA instantiations. Furthermore, following the approach of Webster and Watson [41], a backward search was applied and delivered two additional publications. Therefore, a final number of 19 publications was considered for the analysis.

In step four, the identified literature was analyzed and synthesized (see Section 4). As a final step, the findings were utilized to derive implications for future research.

11.4 Results

Following Webster and Watson [41], identified publications addressing teamwork-specific psychological concepts for the design of CAs are structured with a concept matrix to summarize and analyze the relevant findings. In total, 19 papers were selected, which either focus on general conceptual aspects or CA instantiations. The literature structuring process revealed that the articles at hand cover different teamwork concepts dealing with task or relationship aspects and CA artefacts, which serve different roles. In the following subsections, the results are described in detail.

11.4.1 Conceptual Aspects for CAs

Four publications are concerned with conceptual design aspects of CAs by referring to teamwork concepts. Due to their focus, these articles do not refer to specific CA roles.

Task-focus: Team Processes. With reference to task-focused concepts, two behaviors relating to team processes are specified for artificial agents to reach an effective and a natural form of hybrid teamwork: (1) commit to teamwork by aligning goals to shared objectives and (2) monitor own and collective progress towards shared goals to coordinate interdependent actions [17, 44]. These requirements can be considered as fundamental activities of transition and action processes (coordination, monitoring progress) [29]. In more detail, Castelfranchi [45] addresses the team process of coordinating actions for hybrid teamwork. The author expounds the necessity for artificial agents to coordinate actions with human team members to efficiently exploit knowledge and task-relevant capacities of the individual actors. The proposed central concepts are goal delegation and goal adoption. Depending on a joint task and a corresponding plan, an artificial agent needs to adopt delegated sub-tasks that coincide with the collective's intention to complete a task. Nevertheless, to be considered collaborative, the agent should anticipate flawed plans and proactively modify and align (sub-) goals to the overarching objective.

Task-focus: Emergent States. Klein et al. [17] and Bernard [44] propose that artificial agents should be capable of establishing a mutual understanding by sharing information with members, which is consistent with the concept of shared mental models [27, 32]. To achieve this state, Azevedo et al. [46] point out that artificial agents should explain their actions, decisions and the perceived reactions of the human team members.

Relationship-focus: Emergent States. The work of Azevedo et al. [46] indicates that trust between human and artificial team members needs to be established to improve joint task work. The development of this emergent state is dependent on the artificial agent's ability to convey its understanding of the emotional influence of its actions and decisions on the human team member, which in turn elevates mutual understanding.

11.4.2 Instantiated CAs

Fifteen reviewed publications cover thirteen CA instantiations for hybrid teamwork, as Kumar and Rosé [47, 48] and Kumar et al. [49] report on the same setup.

CA Role. With respect to the different roles, two CA instantiations refer to the role of a facilitator. The instantiated agents proactively tutor, guide and instruct users to achieve a predefined goal or execute a specific task [47–50]. Furthermore, CAs serving the role of a peer were examined in five studies. In accordance to their role, these CAs behave and communicate in the manner of an autonomous team member and are capable of coordinating actions, specifying goals with a human member and monitoring task progress [51–53]. Furthermore, the CAs are capable of proactively managing conflicts and creating shared mental models [54, 55]. Lastly, six studies investigated CAs in the role of an expert, which act predominately reactive. These CAs update and elicit task-relevant information from team members, inform human individuals about the workload state or provide information about conflicting work states [56–61].

Task-focus: Team Processes. Various verbal, behavioral and cognitive activities could be identified in the CA configurations, which pertain to the categories transition, action and interpersonal. The CA, with a restricted dialogue capability, by Harbers and Neerincx [57] incorporates the action process behaviors of team monitoring and backup behavior. In line with this concept, the CA assists team members in finding support (taking over specific activities) by notifying other members that workers with a high workload need support completing their (sub-) task. The CA by Lopez et al. [52] is equipped with a knowledge representation about the task, the team and itself. Due to this technological architecture, the CA is able to reactively respond to human team members' oral questions about current plans to accomplish goals. In addition, the abilities of proactively initiating a joint goal definition process and actively monitoring task progress by asking and informing other team members, the CA executes the action process behaviors of coordination and monitoring progress. In a similar vein, Toxtli et al. [58] developed a CA, which supports team members in keeping track of and coordinating shared tasks. Utilizing natural language in a team chat, TaskBot can delegate tasks to other members on demand, create plans for execution and monitor whether the assignee has completed the task. Sayme, a CA designed by Paikari et al. [61], helps to coordinate team members' interdependent task work by proactively notifying members of a software developer team in a one-to-one chat when the same file is opened or a method is changed by two workers to avoid code conflicts. Similarly, Traum et al. [53] implemented a training scenario in which the embedded CA is able to coordinate joint actions by engaging in dialogues with human team members about plans and team roles. Moreover, Trinh et al. [50] integrated functionalities for the CA to plan the task and assess human team members' progress towards goal accomplishment. In the same way, Aesop, the CA by Meo et al. [51], is capable of monitoring task progress during interactively creating a movie with a user. With its representation of task goals (e.g. character creation), the CA can proactively prompt the user when information is missing.

Task-focus: Emergent States. Two studies address the concept of shared mental models. The CA by Fan and Yen [56], interacts individually with members to update information concerning their acts and beliefs, which in turn are relayed to continuously update shared mental models for the team. In extension to this, Hanna and Richards [55] found out that CAs with an agreeable personality positively affect the development of shared mental models.

Relationship-focus: Team Processes. Three of the reviewed CAs entail configurations, which refer to relationship-focused team processes. Kumar et al. [49] and Kumar and Rosé [47, 48] applied team research insights to implement an interaction strategy for the CA, which builds up users' motivation and confidence by expressing approving (reward, satisfaction, passive acceptance) statements during tutoring. In the same way, the CA developed by Trinh et al. [50] utilizes a conversation strategy to induce motivation by animating users to reconsider their work. Lastly, Kuramoto et al. [54] developed a CA, which is capable of managing conflicts during triangular chat interactions with an employee and a customer. By establishing sympathy with an angry customer, the CA suppresses an anger-filled atmosphere.

Table 4. Teamwork concept matrix

Publications	**Teamwork concepts**																
	Task-focus										**Relationship-focus**						
	Team processes							Emergent states			Team processes			Emergent states			
	Transition			Action				Cognitive			Interpersonal			Affective			
	MA & P	GS	SF	MP	SM	TM & BB	C	SMM	TMS	TC	CM	MB & CB	AM	CO	TT	AT	PS
[17]*				X			X	X									
[44]*				X			X	X									
[45]*				X			X										
[46]*								X							X		
Σ*	-	-	-	3	-	-	3	3	-	-	-	-	-	-	1	-	-
[50]	X			X								X					
[53]							X										
[52]		X		X			X										
[47-49]												X					
[57]						X											
[56]								X									
[58]				X			X										
[61]				X			X										
[51]				X													
[55]								X									
[54]											X						
[59]																X	
[60]														X			
Σ	1	1	-	8	-	1	7	5	-	-	1	2	-	1	1	1	-
Legend	**MA & P**: Mission analysis & planning **GS**: Goal specification **SF**: Strategy formulation			**MP**: Monitoring progress **SM**: Systems monitoring **TM & BB**: Team monitoring & backup behavior **C**: Coordination				**SMM**: Shared mental models **TMS**: Transactive memory system **TC**: Team confidence			**CM**: Conflict management **MB & CB**: Motivation & confidence building **AM**: Affect management			**CO**: Cohesion **TT**: Team trust **AF**: Affective tone **PS**: Psychological safety			

11.5 Discussion and Future Research

As technological advancements pave the way for naturalistic hybrid teamwork between humans and CAs via natural language [1, 9], a human-centered approach is required for the design of CAs. Therefore, the aim of the paper at hand was to make teamwork-specific psychological concepts from team research accessible and usable for IS researchers to design human-centric CAs. For this reason, we systematically reviewed literature on heretofore proposed and utilized concepts for the design and implementation of CAs.

We discovered that the majority of identified publications (13/19) deal with task-related teamwork concepts. More specifically, behaviors are addressed, which are relevant during (action team processes) and prior (transition team processes) to joint task work. Concerning behaviors during task accomplishment, previous investigations show that CAs need a representation of shared plans to flexibly align their goals during task execution [17, 44, 52, 53]. Generally, the artificial team member should act proactively in order to coordinate collective actions and monitor progress towards common task objectives [45, 61]. For coordination purposes, the CA should be capable of detecting flawed plans and present proposals for an alternative course of action accordingly [45]. In addition, to monitor progress of task processes, CAs have to engage in dialogues with individuals to ask and inform other team members about dynamically changing task and workload states [57]. This request for information from individuals by the CA can also serve to monitor the team by relaying relevant disclosures to other members [57]. Referring to the preparation of teamwork (transition team processes), CAs accomplish to identify (sub-) goals by actively initiating goal definition processes with the human team member [52]. At this stage, the CA needs to create a representation of an initial plan and its corresponding goals to warrant successful task execution [50]. Apart from these behaviors, the task-focused emergent state of shared mental models has been previously realized with CAs. This concept can be established by the CA's capability to share task-relevant information [17, 44], describe perceived effects of its own behavior on others and transparently explain its motives for behavior and decisions during teamwork [46]. Furthermore, the development of shared mental models can be positively affected by CA's agreeable personality [55].

A small number of reviewed publications (6/19) cover relationship-related teamwork concepts for CA design. To account for socio-emotional aspects, CAs can positively affect members' motivation levels by encouraging them to reflect on and approving contributions [47–50]. In addition, CAs can assist to resolve conflicts by detecting anger and establishing sympathy between two actors [54]. Regarding relationship-related emergent states, CAs are capable of increasing human team member's emotional engagement by being empathic and personal [59]. Moreover, the transmission of the CA's understanding of the influence of its actions on team members' emotions increases trust [46].

Overall, a small number of previous publications dealt with teamwork concepts in connection with human-centered design approaches for CAs. The reviewed publications show that currently task-related team processes and emergent states are considered to a greater extent than those with a relationship focus. Furthermore, behaviors referring to the preparation of teamwork (transition) and emergent states in general are focused on restrictedly. For the CA instantiations, we observed that none of the CAs incorporate more than three different teamwork concepts, which indicates that CAs do not yet provide full support for teamwork. To expand this research endeavor, we propose general implications for future research. First, the conceptually covered teamwork concepts should be expanded to the described team processes and emergent states to comprehensively inform the design of CAs. More specifically, multiple task-related behaviors should be included by simultaneously considering their temporal sequence (see Figure 1) to allow for flexible hybrid teamwork. Second, the conditions for an efficient delegation and allocation of tasks between humans and CAs should be examined. Third, proposed relationship-related behaviors for joint task work in team research literature should be adopted and intensively examined to account for socio-emotional aspects during teamwork. Fourth, the extension of emergent states to achieve elevated hybrid teamwork outcomes should be pursued.

11.6 Conclusion

This paper covers the current state of research on the application of teamwork-specific psychological concepts and presents knowledge-enriching insights from team research for the design of CAs for hybrid teamwork. Although the conducted literature review contributes to an increased understanding regarding this issue, the results are restricted to articles in the field of information technology, as databases in the domain of human sciences (e.g. PsycINFO) have largely been neglected. Nevertheless, the derived insights constitute a basis for future research and are highly relevant for designers of CAs in science and practice. Overall, the approach of applying well established findings regarding human teamwork is promising to achieve human-centric designs of CAs for hybrid teamwork settings.

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12 Design and Evaluation of a Conversational Agent for Facilitating Idea Generation in Organizational Innovation Processes

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Abstract

Large numbers of incomplete, unclear, and unspecific submissions on idea platforms hinder organizations to exploit the full potential of open innovation initiatives as idea selection is cumbersome. In a design science research project, we develop a design for a conversational agent (CA) based on artificial intelligence to facilitate contributors in generating elaborate ideas on idea platforms where human facilitation is not scalable. We derive prescriptive design knowledge in the form of design principles, instantiate, and evaluate the CA in two successive evaluation episodes. The design principles contribute to the current research stream on automated facilitation and can guide providers of idea platforms to enhance idea generation and subsequent idea selection processes. Results indicate that CA-based facilitation is engaging for contributors and yields well-structured and elaborated ideas.

Keywords: Conversational Agent, Facilitation, Human-AI Interaction, Idea Generation, Open Innovation

12.1 Introduction

Organizations face challenges in discovering and developing innovations due to limited internal resources (Hansen & Pries-Heje, 2017) and the fact that “when focusing on a limited solution space, companies only apply the most obvious instead of the most efficient of all solutions in order to solve an innovation problem” (Lüttgens et al, 2014, p. 342). In this regard, open innovation approaches have been identified to be an effective strategy to improve the efficacy of organizations’ innovation capabilities (Chesbrough, 2003; Lüttgens et al., 2014). Digital platforms, e.g. idea platforms, enable organizations to apply idea sourcing by involving external contributors to access widely dispersed external knowledge and expertise beyond their boundaries (Boudreau & Lakhani, 2013; Cricelli et al., 2021; Di Gangi & Wasko, 2009). However, organizations struggle to harness the potential of idea platforms (Piezunka & Dahlander, 2015), as such idea sourcing initiatives generate highly diverse input whose utilization and valorization remains a key challenge. In particular, the large quantity of contributions pose major challenges in terms of textually unstructured ideas with an insufficient level of detail and indistinct causalities (Barbier et al., 2012; Kipp et al., 2013). As a result, organizations invest a great expenditure of human capacity and time during idea selection to organize and evaluate ideas to select those with high potential (Blohm et al., 2013; Kittur et al., 2013; Merz, 2018). Nevertheless, familiar contributions or ideas with detailed information but little implementation potential might be selected over those with a lack of details and great potential (Bansemir & Neyer, 2009; Piezunka & Dahlander, 2015).

Idea selection could be more efficient, if ideas followed a defined structure to create a common basis to compare them with each other and if they delivered a rich description to establish causalities. One possible way to reach this objective is facilitating external contributors' idea generation process on idea platforms (Briggs et al., 1998; Dennis et al., 1990; Fjermestad, 2000). Previous research has shown that structured facilitation by a human leads to favorable results for collaborative work practices in small teams (Bittner & Leimeister, 2014; Niederman et al., 1996). However, human facilitation reaches its boundaries for large-scale, distributed idea generation on idea platforms as humans can hardly deal with many different parallel work streams and are not constantly available in asynchronous collaboration settings. With the rise of the so-called "Facilitator-in-a-Box" paradigm (Briggs et al., 2013), an approach has been established to shift facilitation tasks from humans to system restrictions and prompts implemented in automated scripts. However, the implementation of such concepts for idea generation runs the risk of discouraging contributors. More specifically, filling various fields in a standard submission form might reduce contributors' enjoyment and cognitive involvement, as they usually do not receive direct rewards via the idea platform (Bretschneider, 2012). Therefore, the user interface and process flow should be designed in such a way that they are engaging for contributors (Attfield et al., 2011) to increase the likelihood of continuing participation while diminishing the detrimental effect of declining motivation levels (Corney et al., 2009; Kim et al., 2013). As idea contributors participate voluntarily, it is therefore paramount to ensure an engaging idea generation process to counteract these adverse effects.

Previous studies have shown increased perceptions of social presence on web-based platforms with virtually embedded social cues (e.g., emotionally rich text, personalized greetings) that approximate face-to-face interactions (e.g., Cyr et al., 2007). In addition, several studies have demonstrated that conversational user interfaces can be rich in social cues (e.g., Pütten et al., 2010). Therefore, contributors' level of engagement and willingness to invest cognitive effort during idea generation could be fostered by the deployment of automated conversation-based facilitation (Schuetzler et al., 2020). To leverage this conversation-based logic, the design of artificial intelligence (AI) involving machine learning (ML) to process natural language can provide an increased level of reactivity and proactivity in comparison to pre-defined time-based sequences of system prompts and state changes. However, the interaction between humans and AI requires more than intelligent algorithms in order to solve specific problems collaboratively and effectively (Harper, 2019; Seeber et al., 2020). In this vein, scholars have recently pointed out that AI-based agents, i.e., in the form of conversational agents (CAs), can be designed to serve the role of a facilitator to support individuals during task execution (Bittner et al., 2019a; Seeber et al., 2018). Moreover, initial research has shown that CAs can guide contributors on idea platforms to generate and submit their ideas in task-oriented conversations (Tavanapour & Bittner, 2018). However, prescriptive design knowledge on how to develop such a solution is still scarce (Bittner et al., 2019b; Diederich & Brendel, 2019; Seeber et al., 2018). Therefore, the following research question is addressed:

RQ: How should a CA be designed and instantiated to facilitate contributors' idea generation and foster their engagement on idea platforms?

Consequently, the aim of this study is to enhance organizations' idea generation via external contributors with a CA as a facilitator and to lay the foundation for improved subsequent organizational idea selection. Therefore. the AI-based facilitation on idea platforms should result in an engaging process to support individuals in voluntarily generating a contribution to an "open call" (Chesbrough & Brunswicker, 2014; Lüttgens et al., 2014) and yield idea submissions with a common structure comprising specific and detailed descriptions. To investigate the potential of the proposed AI-based facilitator for idea generation on idea platforms, the CA concept needs to be instantiated with a software prototype. Thereby, the implementability of the derived design knowledge can be tested with state-of-the-art CA technology. Furthermore, potential effects of facilitation support by CAs during the idea generation process can be explored. Accordingly, in this study, we present a multi-cycle design science research (DSR) project that addresses the stated challenges and research gap with the following structure. First, we present related work about facilitation of idea generation on idea platforms and CAs as facilitators. Second, we outline the research approach by delineating the steps of the DSR project. Third, derived design requirements (DR) and design principles (DP) are described followed by an instantiation of the CA design with a full-featured CA incorporating insights from previous DSR steps. Subsequently, we present the results of the ex-ante and ex-post evaluation stages. Last, we discuss the findings of the study, its limitations, and present an outlook before closing with a conclusion.

12.2 Related Work

12.2.1 Facilitation of Idea Generation on Idea Platforms

By applying the outside-in process, organizations access and utilize external ideas, technologies and/or know-how in one or more of the four phases of open innovation (1) idea generation, (2) experimentation, (3) manufacturing, and (4) marketing and sales (Lazzarotti & Manzini, 2009). In the early phase of organizational innovation processes, idea generation and selection constitute fundamental steps (Hansen & Birkinshaw, 2007; Kornish & Hutchison-Krupat, 2017). To generate ideas, organizations involve external contributors to source their ideas and knowledge (Hilgers & Ihl, 2010; Poetz & Schreier, 2012). Subsequently, a small number of promising ideas are identified and selected to enhance the quality of organizational innovation initiatives (Chesbrough, 2003; Chesbrough & Bogers, 2014; A. King & Lakhani, 2013). To support and improve organizations' process of gathering ideas, well-designed and adequately managed information and communication technology (ICT) can be utilized to provide external contributors the means to share their valuable input with organizations (Bogers et al., 2018; Chatterjee et al., 2021; Gassmann, 2006; Kornish & Hutchison-Krupat, 2017). An established technology to acquire ideas across organizational boundaries represents web-based idea platforms (Di Gangi & Wasko, 2009; Holle et al., 2016). However, despite the benefit of rapidly gathering and exploiting innovation ideas, organizations face several challenges in managing this ICT to fuel their innovation processes.

First, the lack of knowledge about mechanisms to enhance contributors' motivation has led to research about user engagement (Füller et al., 2008; Kosonen et al., 2013). This concept is defined as "a quality of user experience (UX) that is characterized by the depth of an actor's cognitive, temporal, and/or emotional investment in an interaction with a digital system" (O'Brien & McKay, 2018, p. 73). With user engagement, a continuing participation can be established through involving and captivating individuals, which produces positive affective reactions, a focused attention, and motivation through novel experiences. In this regard, studies have shown that user engagement in open innovation initiatives can be positively influenced by the design of an interface (Attfield et al., 2011), the presentation of a task (Benz et al., 2019), and the clarity of the task goal (T. de Vreede et al., 2013). Second, large amounts of collected ideas and the absence of strategies to systematically converge them has provoked research about the idea selection step of innovation processes (Dellermann et al., 2018; Merz, 2018; Seeber et al., 2017; G.-J. de Vreede et al., 2021). More specifically, research has identified the challenge for organizations with limited absorptive power (e.g., time constraints, limited cognitive resources) to select valuable ideas from a large pool with varying attributes (e.g., specificity, comprehensibility) (Schulze et al., 2012), as an extensive proportion is incomprehensible and unstructured (Bjelland & Wood, 2008; Blohm et al., 2013). In this respect, the investigation of organizational idea selection strategies in open innovation initiatives has shown that several strategies involving different agents are applied (Haller et al., 2017; Merz, 2018). Ideas can be selected either by (1) an external crowd, (2) a small team comprising different stakeholders, (3) a specialized algorithm, or (4) a hybrid team consisting of an algorithm and crowd or a small team (Merz, 2018). However, regardless of the involved agents, a lack of mechanisms to make the selection process as efficient as possible to select the best idea(s) has been identified (Merz, 2018).

As the structure and richness of ideas in platform-based settings has been shown to be significantly lower compared to those generated in facilitated focus groups (Schweitzer et al., 2012), the structured guidance of individuals' idea generation could provide more consistent idea attributes. Accordingly, idea selection could be improved, independently of the involved agents, by guiding contributors during idea generation to gather contributions with a pre-defined set of required information. Thereby, contributors' difficulty in providing relevant information and necessary details to increase the implementation likelihood of their idea can be counteracted (Li et al., 2016). Moreover, contributors could be assisted socio-emotionally, as constructive feedback and emotional support have been shown to positively affect individuals' idea generation (Perry-Smith & Mannucci, 2017; Schweitzer et al., 2012). Consequently, to leverage these effects, facilitation can be utilized to enable structural guidance while simultaneously considering socio-emotional factors and a systematic documentation of ideas.

The concept of facilitation is defined as interventions in a structured and dynamic process that are executed by a designated person with the main goal to guide members of a group towards efficiently achieving their common goal (Bostrom et al., 1993; Clawson & Bostrom, 1996; Kelly & Bostrom, 1997). Facilitation has shown the potential to produce high quality group outcomes in face-to-face meetings (Bittner & Leimeister, 2014; Bowers et al., 2000; Langan-Fox et al., 2004). Furthermore, with the raise of group support systems (GSS), the role of the facilitator has been extensively investigated in the context of ICT-mediated meetings (Clawson & Bostrom, 1996; Clawson et al., 1993; Kelly & Bostrom, 1997). In the "Facilitation Framework" of Bostrom et al. (1993), previous findings have been consolidated to describe necessary actions of a digital facilitator. The framework distinguishes three sets of activities that are executed by a facilitator: (1) process, (2) task, and (3) relationship (Bostrom et al., 1993). Process related facilitation activities (How?) serve to support the accomplishment of tasks (What?) by individuals. Relationship facilitation (Feel about) influences the relational outcome during this process. As an extension to previous research, the "Facilitator-in-a-Box" paradigm has been developed to automate facilitation processes and substitute a human facilitator with a pre-defined sequence of system prompts and state changes (Briggs et al., 2013). However, this approach neglects the conversational nature of facilitation and socio-emotional dimensions of facilitative activities. In order to cover all facilitation dimensions (process, task, and relationship), evolving ML-based AI technology in the form of CAs represents an applicable solution to automate the facilitation of users' idea generation (Seeber et al., 2018).

Overall, an AI-based CA facilitation could meet organizations' requirement to effectively manage and implement emerging technologies to establish an approach to efficiently source and select external ideas (Kornish & Hutchison-Krupat, 2017) by utilizing a structured and engaging idea generation process.

12.2.2 Conversational Agents as Facilitators

CAs are software systems that are capable of interacting with humans via natural language in a dialogical fashion (Araujo, 2018; Bittner et al. 2019b; Diederich & Brendel, 2019). The concept of CAs is inspired by the idea to emulate naturalistic text- or speech-based conversations between intelligent machines and humans by analogy to human interaction (Elshan et al., 2022; Laumer et al., 2019; McTear et al., 2016). Different terms have been utilized for CAs (e.g., virtual or cognitive agent, dialogue system, and chatbot or chatterbot) referring to the modes of either spoken or written interaction and interactive or static forms of representation (Gnewuch et al., 2017; Hill et al., 2015; Shawar & Atwell, 2007). The capabilities of CAs have steadily evolved over the years. The initial CA ELIZA responded with questions to requests by analyzing users' input to find pronouns and turn them into the opposite (Weizenbaum, 1966). Since then, technological advancements in the fields of ML and natural language processing (NLP) have led to a significantly improved pattern recognition in human language which has elevated CAs' capabilities to identify responses matching to users' input (Io & Lee, 2017; Knijnenburg & Willemsen, 2016). This technological progress enables more human-like interactions with CAs (Nguyen et al., 2021). Nevertheless, naturalistic interactions are not yet fully feasible due to the complexity of natural language conversations (Ashktorab et al., 2019; Schuetzler et al., 2021; Shah et al., 2016). Misinterpretation of user input, incorrect responses, and tedious interactions often fail to meet users' high expectations of conversations with CAs (Luger & Sellen, 2016). To counteract this potential dissatisfaction, dialogs are designed to be engaging in order to encourage users to continue a conversation despite erroneous interactions (Grudin & Jacques, 2019; Schuetzler et al., 2020).

In research, two general streams focus on different types of CAs. On the one hand, studies concentrated on developing and investigating general CAs that should be capable of reacting to any utterance by a human counterpart with a suitable solution or answer (Gnewuch et al., 2017; Hill et al., 2015). On the other hand, a growing body of literature has evolved on domain-specific CAs. With a limited knowledge base, these CAs are used in specific application domains such as education, customer service, finance, human resources, and health care (Følstad et al., 2019; Janssen et al., 2020). In the latter research stream, domain-specific CAs have already been utilized to provide facilitation toward accomplishing specific goals or to structure conversations for well-defined, recurring tasks. For example, prior studies have shown that triggers in the form of questions posed by a CA induce favorable behavior in terms of reasoning and elaboration in computer supported cooperative learning (Kumar & Rosé, 2014; Tegos et al., 2014, 2015) and citizen participation (Ito et al., 2021). Furthermore, Wang et al. (2007) demonstrated that a virtual agent could support an individual during idea generation, which resulted in more ideas in comparison to interactions between two humans. Louvet et al. (2017) proposed an interaction process model, where the agent is able to express requests for precision, reformulation, or verbalization in reaction to certain triggers. Complementing and extending these previous studies about automated facilitation, the study at hand focuses on facilitation by a CA that supports external contributors to submit an elaborated idea to an open call and structures their idea generation process on idea platforms. Therefore, we introduce a definition for a CA facilitator which bases on various related definitions. As Lieberman (1997) defines an agent as a program that acts as a facilitator rather than a tool and Bailenson and Blascovich (2004, p. 65) refers to it as "a perceptible digital representation whose behaviors reflect a computational algorithm designed to accomplish a specific goal or set of goals", a CA facilitator can be defined as an intelligent artificial agent that is capable of guiding through a structured process utilizing natural language to support an individual or group to achieve a common task goal.

With the objective of developing an AI-based CA with a static representation that interacts via written language serving the role of a facilitator, the presented study aims to contribute to the stream of research about domain-specific CAs (Bittner et al., 2019b). To achieve this, the design of a CA facilitator needs to be informed with meaningful insights from research on behavioral aspects that affect its facilitation capabilities. Studies in this field have, inter alia, shown that social cues which mimic human behavior are beneficial to support task- and productivity-related aspects (Medhi Thies et al., 2017; Morrissey & Kirakowski, 2013; Nunamaker et al., 2011). Moreover, recent research derived application-oriented design knowledge to guide research attempts in developing CAs as facilitators for idea generation processes (Strohmann et al., 2018; Tavanapour & Bittner, 2018). Apart from these preliminary investigations, the design and development of CAs in the domain of idea sourcing has not been extensively addressed and needs to be intensified (Diederich & Brendel, 2019).

12.3 Research Approach

In order to address the research aim of assisting and engaging contributors during idea generation to lay the foundation for a systematized selection of submitted ideas, we conduct a DSR project with multiple consecutive design cycles (see Fig. 1) (Gregor & Hevner, 2013; Vom Brocke et al., 2020). With the design and development of an artifact in the form of a full-featured CA facilitator incorporating insights from previous design cycles, we intend to provide a novel and innovative solution to the prevalent real-world problem of unsystematized and insufficiently engaging idea generation processes that are commonly deployed for open innovation initiatives. To ensure research rigor and generate substantial prescriptive design knowledge, we follow the established iterative six-step approach by Peffers et al. (2007).

Two preceding design cycles were completed to iteratively approach the identified problem. The scope of the first cycle was to gain exploratory knowledge about automated facilitation for idea generation with a CA. Correspondingly, micro and macro scripts were defined to generate tentative design knowledge in the form of interaction scripts (Gregor

& Hevner, 2013). The macro script serves to define the process sequence and conversation flow, whereas the micro script specifies relationship-related aspects (e.g., affirmative statements, motivational explanations) for the CA facilitation. To assess the potential of the interaction design for a CA facilitated idea generation process, a Wizard-of-Oz (WoO) experiment was performed (Kelley, 1983). For this purpose, uninformed participants interacted with an undisclosed human wizard, who used the micro and macro scripts to facilitate the idea generation process. The wizard controlled the system to make the participants believe that they are interacting with a CA. The results of the WoO experiment, on the one hand, served as a proof-of-concept for follow-up investigations. On the other hand, the findings were used to inform the improvement of the conceptual CA design. The first cycle was completed by communicating the derived insights (Bittner et al., 2019a).

Guided by the validated micro and macro scripts, an initial CA prototype was developed for automated facilitation on idea platforms. Based on the conversation protocols from the WoO experiment, data was derived to train the open-source NLP framework Rasa[1] for the CA prototype. For the design, DRs were identified with a comprehensive literature search according to Webster and Watson (2002) drawing on justificatory knowledge from the fields of AI, NLP and ML. The prototypical CA was evaluated with a user test. The communication of initial design knowledge and evaluation results completed the second cycle (Tavanapour & Bittner, 2018).

	Cycle one	Cycle two	Cycle three
(1) Problem identification	Problem relevance: literature-based identification of problem(s) connected to idea submission	Reflection and refinement of problem relevance	Reflection of preceding cycle
(2) Objectives of a solution	Automated facilitation of idea submissions with CAs	Comprehensive literature search for derivation of DRs	Refinement of DRs and development of DPs (see section 4)
(3) Design & development	Interaction design concept for CA facilitation based on micro and macro scripts	Lightweight CA prototype based on micro, macro scripts, and DRs	CA implementation based on DPs (see section 5)
(4) Demonstration	Simulation of the interaction script for CA-based facilitation	Pre-test with selected users	Ex-ante evaluation with expert focus groups and users (see section 6)
(5) Evaluation	Experiment (Wizard of Oz) with quantitative evaluation to provide proof-of-concept	User test with quantitative evaluation of CA prototype for initial proof-of-applicability	Ex-post evaluation with a mixed method approach (see section 7)
(6) Communication	Bittner et al. (2019a)	Tavanapour and Bittner (2018)	Report and embed findings in knowledge base

Figure 1. DSR approach based on Peffers et al. (2007) with current cycle in white

The third cycle represents the focus of this publication. The objective is to combine and extend insights from the first two cycles to address the joint problem identification of this DSR project. Step one (*problem identification*) has been addressed in the introduction and related work section. In the second step *objectives of a solution*, previous tentative prescriptive knowledge is expanded by developing DPs, which are based on extended and refined preliminary DRs from cycle two. This revision builds on a literature-based

[1] https://rasa.com/

derivation of requirements and an analysis of results from the evaluation in the preceding cycle. In the third step *design and development*, the DPs are instantiated. Informed by derived DRs a revised and full-featured version of the CA facilitator is implemented. To this end, training data from cycle two is updated with refined intents and entities to improve the performance of the NLP module of Rasa. Moreover, micro and macro scripts from cycle two were utilized to construct the facilitation process sequence of the instantiated CA. Regarding steps four and five, an evaluation of the design comprising ex-ante (*demonstration*) and ex-post stages (*evaluation*) is conducted (Venable et al., 2016) (see Table 1). With the ex-ante evaluation, the applicability, operationality, and completeness of the designed artifact for the described problem statement of the DSR project is demonstrated (Sonnenberg & Vom Brocke, 2012). In this evaluation activity, exploratory focus groups (EFG) were conducted to obtain valuable input and modify the design and corresponding functionalities of the CA (Nielsen, 1997; Tremblay et al., 2010; Venable et al., 2016). Therefore, the DPs and their instantiation in the CA were presented, tested, and discussed in two focus groups with potential users (four participants, 59 min. duration) and researchers with different contextual knowledge (software developers, CA/AI experts) (five participants, 91 min. duration) (see Sect. 6). To perform a naturalistic ex-post evaluation, a two-fold strategy is applied to leverage an extensive set of empirical data and gain insights on the efficiency and feasibility of the instantiated DPs (Venable et al., 2016). First, data on characteristics of submitted ideas from real users was gathered. For this purpose, the CA was deployed on a website during a research project involving partners from research and practice in the field of public administration. After initiation of the open call by several project stakeholders, 40 external participants submitted an idea on the topic "Mobility of the Future". Based on these submissions, the characteristics of the ideas were examined, on the one hand, in semi-structured interviews with four experts from, inter alia, the fields of innovation and product management. On the other hand, a computer-based analysis was conducted to investigate the linguistic attributes of the collected ideas to draw inferences about the affective and cognitive processes of the idea contributors. Second, the CA facilitator and a standard submission form for idea generation were compared to assess the level of engagement and perceived social presence induced in potential idea contributors. Therefore, 221 participants were divided into two conditions to observe one animated mock-up simulating the respective idea generation process. Subsequently, participants completed a questionnaire-based evaluation of the simulation. Step six (*communication*) will be completed with the publication of this study.

Being part of a multi-cyclic DSR project (see Fig. 1), this research aims to make a two-fold contribution by providing prescriptive design knowledge and a corresponding design entity in the form of an instantiated CA facilitator (Drechsler & Hevner, 2018; Gregor & Hevner, 2013). Besides codifying the functioning and construction of the artifact, the utility character of the generated design knowledge is established via the comprehensive evaluation (Kuechler & Vaishnavi, 2012; Venable, 2006). In the following sections, we elaborate on the delineated steps of the third cycle of the DSR project covered in this publication.

Table 1. Outline of the different phases of evaluation, purposes, methods, and participants, and references to the respective sections

Evaluation stage	Evaluation purpose	Applied method	Participants	Number of participants	Section
Ex-ante	Evaluation of design and functionality of CA	EFG	EFG1: Potential users EFG2: Researchers	EFG1: 4 EFG2: 5	6.
Ex-post	Evaluation of CA facilitated ideas	Qualitative expert interview	Experts in the domain of open innovation	4	7.1.1.
		Computerized linguistic	-	-	7.1.2.
	Evaluation of CA facilitated idea generation	Quantitative survey	Potential users	221	7.2.

12.4 Objectives of a Solution

12.4.1 Design Requirements for a CA Facilitator

The development of CAs requires scientifically substantiated design knowledge (Amershi et al., 2019; Diederich & Brendel, 2019). To determine characteristics and behaviors of a CA facilitator in the form of DRs to deduce DPs, extant literature was analyzed, and suitable theoretical insights were incorporated. The principal theoretical basis for the proposed design builds on the Social Response Theory (Nass & Moon, 2000) and Social Presence Theory (Daft & Lengel, 1986; Gefen & Straub, 1997; Short et al., 1976). The Social Response Theory postulates that individuals unconsciously apply social rules to computers if they perceive social cues that are associated with human attributes or behavior, whereas the Social Presence Theory refers to the perception of humanness in a medium determined inter alia by its communication richness. According to these theories, CAs' anthropomorphic characteristics evoke unconscious social responses in users due to their virtual identity and capability to interact via natural language (Gong, 2008; Pütten et al., 2010). These responses, combined with the application of social rules, fuel users' expectations of human-like behavior toward CAs. Consequently, a design approach is required that affords CAs' human-like facilitation behavior supported with current technological capabilities of AI. With regard to these principal theories, the derivation of DRs was structured with the "Facilitation Framework" of Bostrom et al. (1993), as this framework summarizes relevant facilitation skills categorized into several acts that are directed toward the *task* at hand, the *process* to achieve the associated goal, or the *relationship* between facilitator and participants.

With *process* and *task*, facilitative acts are addressed which refer to the capabilities of supplying instructions about the task, providing relevant information, and guiding through a process (Clawson & Bostrom, 1996; Clawson et al., 1993). Therefore, a CA facilitator should present the task and associated steps to initiate the process (*DR1.1*) (S. Kim et al., 2020). In addition, the CA facilitator should ensure that users follow the idea generation process and guide them with goal-oriented behavior to assure the achievement of an idea submission (Clawson & Bostrom, 1996). In this regard, Morrissey and Kirakowski (2013) showed that CAs' construction of engaging conversations leads to elevated levels of user acceptance and productivity, which leverages substantial input (Tegos et al., 2014). Accordingly, the CA should take initiative to actively direct and lead the conversation to support users in the process (*DR1.2*) (Jain et al., 2018; Montero & Araki, 2005; Morrissey & Kirakowski, 2013; Nouri et al., 2020). To ensure productivity-oriented behavior that promotes users' engagement and motivation (Brandtzaeg & Følstad, 2017; Medhi Thies et al., 2017), the CA has to prevent conversations from ending at critical points by asking smart, suitable, and process-relevant questions (*DR1.3*) (Montero & Araki, 2005). In extension to this, the CA should prompt users to edit initial or enrich missing input (*DR1.4*) (Morrissey & Kirakowski, 2013; Tegos et al., 2014). Another relevant characteristic of facilitators referring to process-related acts is their ability to assure an optimal outcome by maintaining the focus on the defined task goal (Clawson & Bostrom, 1996). Thus, the CA should, on the one hand, prevent deviations from the conversation topic to avoid flops in dialog flow or process phases and be aware of the current task state by tracking users' progress (*DR1.5*) (Liao et al., 2018; Nouri et al., 2020; Poser & Bittner, 2020). On the other hand, CAs should be capable of flexibly reacting to users' utterances regarding the present phase of the process by providing information and explanations on demand about the current activity and specific terminology to ensure users' understanding of and engagement with the task (*DR1.6*) (Schuetzler et al., 2018).

Regarding *relationship*-focused acts, facilitators provide an open and positive atmosphere to engage people in the process and task at hand (Bostrom et al., 1993; Clawson et al., 1993; Kelly & Bostrom, 1997). As the utilization of natural language increases users' perception of artificial entities' humanoid characteristics (Nass & Moon, 2000), the CA should emulate human-like and reciprocal conversational behavior that is adjusted to a specific audience to strengthen users' trust, enjoyment, and perceived usefulness (*DR2.1*) (Gefen & Straub, 1997; Hassanein & Head, 2007; Johannsen et al., 2018; Knijnenburg & Willemsen, 2016). In doing so, the CA should create a positive dialog environment by following a socio-emotional facilitation style. More specifically, the CA should foster engagement, confidence, and show sensitivity by making approving and motivating statements during the process (*DR2.2*) (Jenkins et al., 2007; Nimavat & Champaneria, 2017; Portela & Granell-Canut, 2017; Poser & Bittner, 2020). To intensify the positive atmosphere and personalize the relationship with users, CA's linguistic cues and style should increase friendliness perceptions (*DR2.3*) (Adams et al., 2012; Araujo, 2018; Medhi Thies et al., 2017; Verhagen et al., 2014). Accordingly, the CA should use informal language as well as typical dialogical cues such as greeting the user and wishing farewell (*DR2.4*) (Araujo, 2018). In addition, users' names should be captured to reference it during the interaction (*DR2.5*) (Johannsen et al., 2018).

These facilitation-related design aspects need to be enabled by CAs' general technical capabilities. Therefore, a CA facilitator should be able to construct a conversation and recognize users' intentions and deliver adequate reactions to ensure successful task accomplishment (*DR3.1*) (Ghose & Barua, 2013). As the interaction with users should imitate human conversational behavior, pre-set answers via buttons should not dominate the dialog and the CA should have a short, human-like response latency (*DR3.2*) (Acerbi et al., 2010; Diederich et al., 2019; Gnewuch et al., 2018; Loftsson et al., 2010; Zamora, 2017). Furthermore, CA's conversation texts should be short understandable, and characterized by correct grammar and spelling (*DR3.3*) (Morrissey & Kirakowski, 2013; Salomonson et al., 2013). Moreover, the CA should be equipped with intervention strategies to proactively trigger user actions in adequate situations, such as silent moments (*DR3.4*) (Morrissey & Kirakowski, 2013; Tavanapour & Bittner, 2018).

12.4.2 Design Principles for a CA Facilitator

The identified set of DRs was utilized to derive four DPs (see Fig. 2). Following a supportive approach, 15 DRs were elicited based on insights from the knowledge base to develop the DPs of the type form and function (Chandra et al., 2015; Möller et al., 2015). The resulting DPs are categorized according to the classification of facilitative acts by Bostrom et al. (1993) differentiating between process and task, or relationship.

Process and task: To facilitate users during the idea generation and submission process, the CA should be able to initiate a conversation by supplying relevant information about the task and steps to subsequently direct and lead users in a productivity-oriented and pleasant manner by posing questions and preventing deviations to other topics (*DP1*). The directed facilitation process should yield elaborated outcomes. Therefore, the CA requires capabilities to react to and motivate the user in different situations or offer support on demand by delivering explanations about the process steps and topic-related terms (*DP2*). To efficiently facilitate users through the idea submission process, the CA must be equipped with technical capabilities. The CA needs NLP capacity to correctly identify users' intentions and respond with pre-defined, understandable, short messages with excellent grammar and spelling in a short amount of time. Moreover, the CA requires a strategy to counteract silent moments by proactively offering support when users are inactive for a certain period of time (*DP3*).

Relationship: For the provision of a positive dialog environment during the facilitated idea submission process, the CA should offer socio-emotional support by motivating and approving users' input. In addition, to foster users' acceptance, the CA should develop a personalized interaction, act friendly, polite, and utilize informal language (*DP4*).

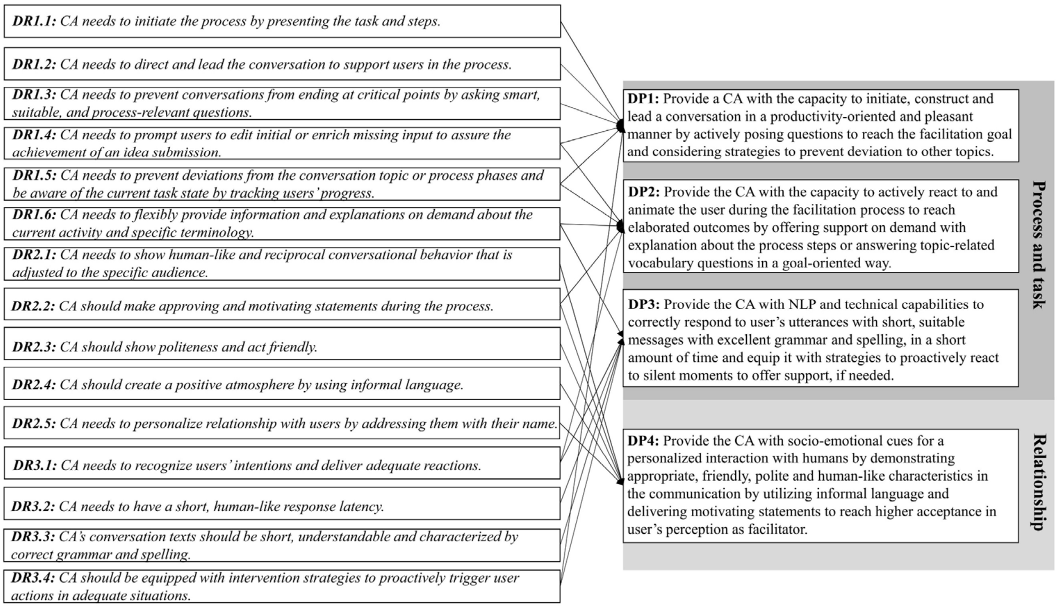

Figure 2. Design requirements (DR) and corresponding design principles (DP)

12.5 Design and Development

12.5.1 CA Development

The development of the CA facilitator was guided by the micro and macro scripts from cycle one. The macro script served to determine the process sequence and conversation flow, whereas the micro script defines relationship-related aspects for the CA facilitation. Accordingly, the facilitative acts *[1] introduction*, *[2] generate*, *[3] build consensus*, and *[4] closing* from the macro script were implemented to develop the logic of the process and conversation flow. The CA follows the depicted sequence of steps in Fig. 3: In the *[1] introduction* the user is asked to indicate the desired form of address (name vs. anonymous), the number and content of process steps are explained, and the idea generation process is started, if desired. In *[2] generate*, the CA poses questions to record the ideas. To reassure the correctness of idea items and allow users to edit content, the CA shows a summary in *[3] build consensus*. Lastly, in *[4] closing*, the CA expresses farewell. In line with the micro script, CA's utterances across all macro script steps include affirmative feedback (e.g., "Thank you very much!"), motivational explanations (e.g., "For others to understand your idea well, you should describe it as clearly as possible.") and general reactions (e.g., "I'm sorry. Unfortunately, I do not have a suitable answer to your input.").

To develop the CA according to the macro script logic, the open-source framework Rasa was used. This allowed to fulfill research-related constraints such as expandability and sovereignty over data. The Rasa framework is divided into the submodules Rasa Core and Rasa NLP. Rasa Core is responsible for administrating the dialog flow and Rasa NLU for processing natural language. The dialog structure is modeled by a finite set of intents, entities, and slots. Intents are utterances with which the user confronts the CA. Entities represent the information the CA extracts from the conversation. Rasa NLU recognizes the intents and entities from the messages sent by the user. Rasa Core directs the dialog flow and triggers actions that correspond to the intents. The recognized entities are stored in the respective slots. In our case, the intents and corresponding training data were derived from previous studies in cycles one and two. The eight slots (S1-8) of the CA are filled sequentially during *[1] introduction* and *[2] generate* from the macro script (see Fig. 3).

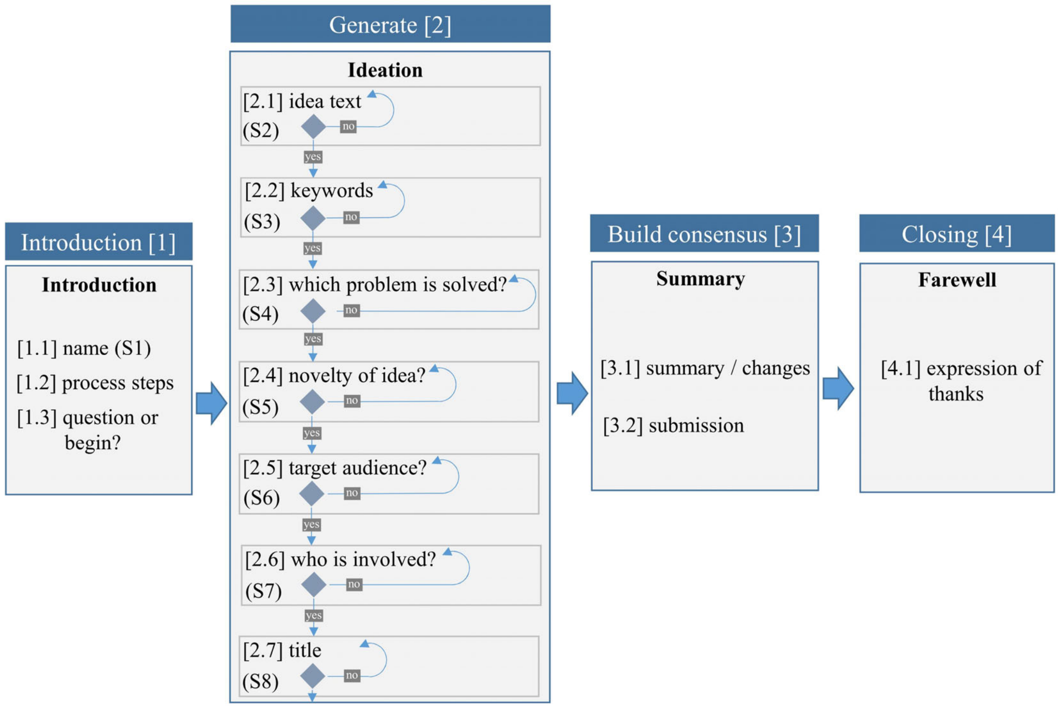

Figure 3. The logic of the CA facilitation in accordance with the macro script

The first slot refers to the name of the participant, which is registered, if indicated by the user. The remaining slots (S2-S7) correspond to the seven previously identified relevant items of an idea: (S2) idea text, (S3) keywords, (S4) which problem is solved, (S5) novelty of idea, (S6) target audience, and (S7) title (Bittner et al., 2019a). To facilitate users and react to their input in a suitable manner, the CA is designed to identify different intentions in users' input during *[2] generate* (see Fig. 3). More specifically, the CA can, corresponding to DP2, differentiate between five different categories of questions posed by the user referring to the topic, task, or process by recognizing terms and vocabulary and reply with appropriate answers. In accordance with DP3, the CA can detect silent moments and react by offering support. The silent moment was set to trigger after five minutes of inactivity, which has proven to be a meaningful threshold for activating users (Tavanapour & Bittner, 2018). In addition, the CA can detect users' intentions of aborting the process and offers to end the process. Most importantly, the CA can actively lead the conversation by posing questions to fill the slots (S2-8) (see Figs. 3 and 4). If the CA was not successful in filling a slot due to a different intention of the user (e.g., a question referring to specific terms), the CA repeats the question for that slot until it was successfully filled. In case users abort the facilitation process before it is completed, the input for the slots filled up to that point is saved.

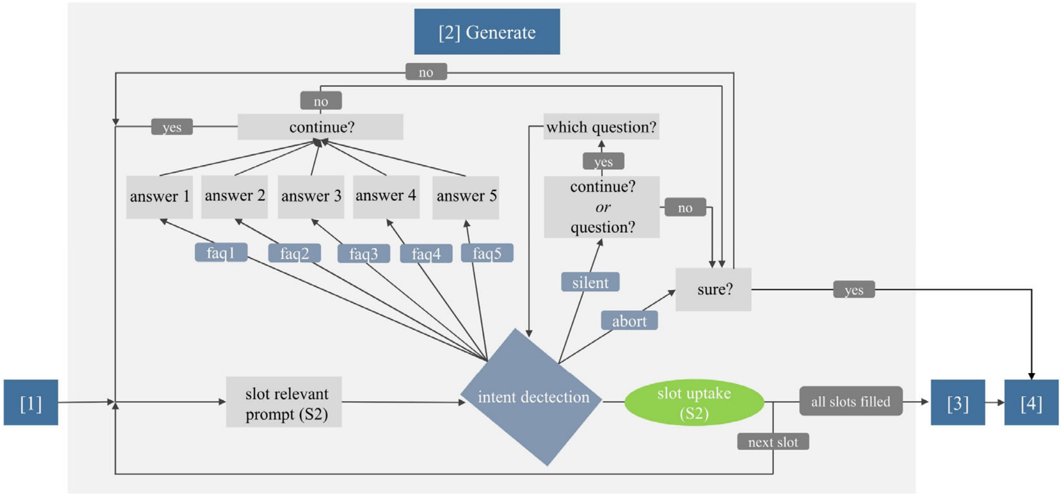

Figure 4. The facilitation logic of the implemented CA

12.5.2 Instantiation of the CA Facilitator

For the implementation of the CA facilitator, the defined DPs were matched to artifact features that cover the specifications of the prescriptive knowledge and the depicted architectural settings in Figs. 3 and 4. Once triggered by a user, the CA initiates a conversation in line with the DPs and facilitation acts of the macro script. The implementation of the dialog management was supported with pre-set response options to sustain the process logic of the CA facilitation. Figures 5 and 6 visualize several functionalities of the CA during an exemplary conversation (translated from the original language) with a user. The conversation snippets show the CA a) introducing into the process, b) leading the conversation for the idea generation process, and c) reacting to a question regarding a specific term or to a silent moment. Furthermore, in d) the editable summary is depicted.

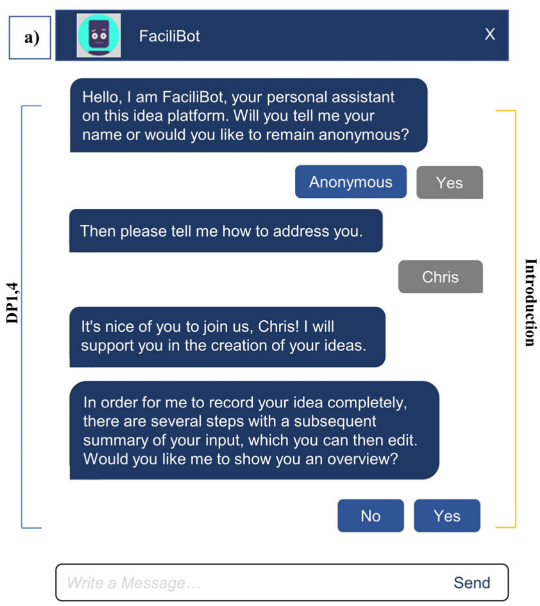

Figure 5. Conversation snippet of the CA facilitation with corresponding DP and facilitation act

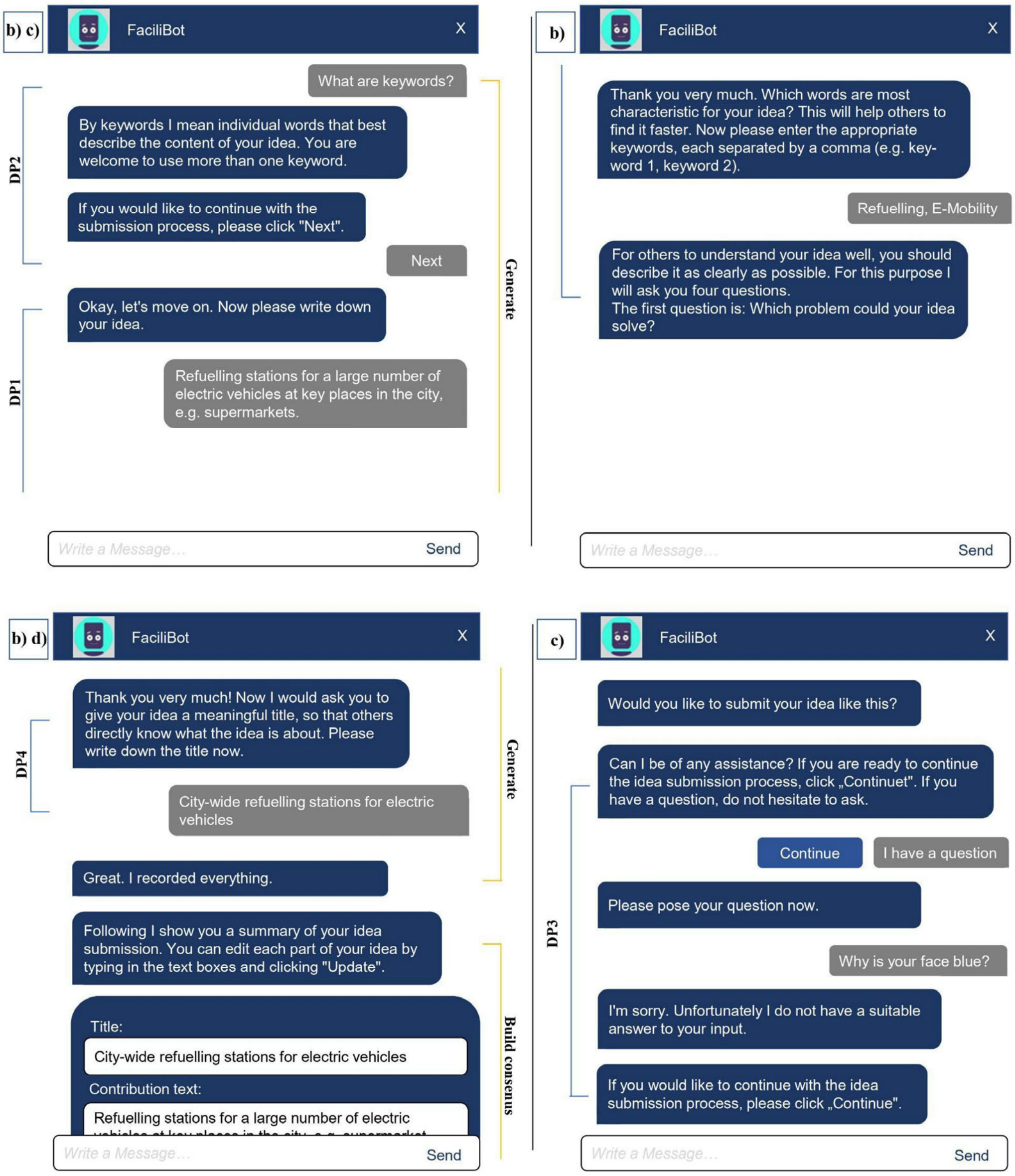

Figure 6. Conversation snippets of the CA facilitation with corresponding DPs and facilitation acts

12.6 Demonstration

The ex-ante evaluation episode focuses on the formative assessment of the created and instantiated design in the form of an automated conversation-based CA facilitation to purposefully address the identified real-world problem of unsystematized idea submissions due to limited support for contributors during the idea generation process (Sonnenberg & Vom Brocke, 2012; Venable et al., 2016). To evaluate the applicability, operationality, and completeness of the created and instantiated CA design, we utilized EFGs to leverage a rich qualitative data set.

Following the proposed steps by Tremblay et al. (2010), we conducted two EFGs to obtain profound feedback on design-related aspects as well as technical functionalities of the initial CA version. The first focus group (EFG1) lasted 59 min and consisted of four participants, each of whom had participated at least once as a contributor in an open innovation initiative. Accordingly, the two female and two male participants represent potential CA users. The second focus group (EFG2), which comprised five male participants from research with expert knowledge in software development of CAs and/or AI, lasted 91 min. Each focus group was recorded and followed a pre-defined procedure: (1) presentation, (2) demonstration, and (3) discussion. In the first phase, the context and objective of the study was presented. Subsequently, participants individually conducted a click-through and executed functional tests to evaluate the CA during the idea generation task. After that, a prepared guideline with open-ended questions based on the four DPs was utilized to validate and refine the design. Based on transcripts, a qualitative content analysis according to Mayring (2014) was individually conducted by two researchers and resulting codes were continuously harmonized to obtain insights about the DPs and derive opportunities for improvement.

In general, the analysis of qualitative data showed that participants of both focus groups rated the CA facilitator as applicable and operational to record and select ideas in a homogenized format for further processing. The user interaction was described as flawless, intuitive, engaging, and human-like. The participants rated the interactive questioning process as detailed, coherent, and targeted. Furthermore, they reported that the submission of an idea was supported by the transparent progress in the process (e.g., “The process design is designed in such a way that it can be followed very firmly, and it is also developed in such a way that the process can be easily tracked” (EFG2)). With reference to *DP1*, the participants assessed the requirements to be clearly outlined, the posed questions by the CA to be very goal-oriented, and the process design to be easy to follow. The logical step-by-step approach helped “writing things down, which is good when developing a spontaneous idea” (EFG1). Therefore, participants had “the feeling of being guided toward reaching a goal” (EFG2). Moreover, the participants agreed that “CA’s utterances build upon each other” (EFG2) and are suitable for the task of facilitating the idea generation process. For *DP2*, participants valued the flexible interaction and possibility to ask questions, although only a few of them used this functionality. The CA’s intention to acquire elaborated input was recognizable, e.g., “when he asked whether I would like to confirm or change specifications” (EFG2). In addition, participants considered the support with optional information about the topic at the beginning of the process to be valuable. The “definitions and further instructions during the process steps were goal-oriented, when asked for” (EFG1). In relation to *DP3*, the user guidance was judged to be well-managed with clearly formulated, precise, and understandable statements and questions. According to the participants, the content of the messages had a suitable length and language level, keeping mental effort at minimum level. In this context, one participant affirmatively stated that “it was easy to follow, it was very clear what was meant and there was little room for misinterpretation” (EFG2). During the click-through demonstration, the CA reacted correctly with prompt responses which was perceived to sustain the progression through the process. While participants rated the strategy of the CA to counteract silent moments as generally useful, the implementation was rated to require improvement, as one participant experienced a mistakenly triggered reaction by the CA: "I wrote a long text and was already asked before sending it" (EFG2). Regarding *DP4*, participants stated that they were aware of interacting with a CA. Nevertheless, the text-based and friendly conversation was considered conducive to the atmosphere, as it conveys a sense of humanness. One participant commented: "the natural language equilibrates and pulls it away from a pure technical impression" (EFG1). Furthermore, statements from the CA between process phases were perceived as motivational support. The interactivity of the process was regarded to reduce the initial hesitation of starting to submit an idea. The personal address created sympathy among participants for the CA. In particular, referring to the user by name during the process had a positive influence, as one participant reported: "it gives a personal touch, and I am a person who likes to be called by my first name" (EFG1). With the tentative CA version, the completeness of relevant design aspects could be demonstrated. In addition to confirming insights, focus group members highlighted potential for improvement related to support behavior and technical features of the CA. To increase the advantage of support upon request, the CA should clearly indicate how and for what purpose. The silent moment should not be triggered too early when users are actively making entries, as this unnecessarily interrupts the writing process. From a technical perspective, "the interaction capability is expandable" (EFG2). Accordingly, the language model requires fine-tuning, since intents were sometimes recognized incorrectly and participants were occasionally offered process termination. To encourage users to write extensive and detailed ideas, the entry field should be larger, since "it is better if one has the possibility to see the multiline text" (EFG2).

12.7 Evaluation

For the ex-post evaluation, an adapted and improved CA facilitator was implemented based on the findings from the demonstration. To gain insights into the efficiency and feasibility of the instantiated DPs, we conducted a naturalistic evaluation of the final artifact (Creswell et al., 2003; Sonnenberg & Vom Brocke, 2012; Venable et al., 2016). To this end, we completed two field studies and applied various evaluation activities. On the one hand, we deployed the CA facilitator on a website to gather submissions from real users and subsequently analyze the characteristics of the ideas (see Sect. 7.1.). On the other hand, we assessed the feasibility of the proposed solution to engage contributors and provoke a perception of social presence by comparing the levels of engagement and social presence of CA facilitation with a standard submission form.

12.7.1 Evaluation of Ideas

To gather data on characteristics of CA facilitated ideas from real users, we initiated an open call during a research project involving partners from research and practice in the field of public administration. The call on the topic of "Mobility of the Future" was distributed via different university and city mailing lists, social media, and student groups to invite a wide group of participants to generate ideas. Guided to a website via link in the open call, participants were provided with information about the subsequent task and the possibility of winning vouchers. The topic was presented in the form and length of an abstract describing advantages and disadvantages of current mobility solutions. The participants were asked to propose ideas for a change of mobility at the national level. The idea generation process with the CA could be started by clicking a designated button. In total 40 ideas could be collected and served as data for a two-fold idea evaluation, reported in the following. First, interviews with domain experts were conducted to qualitatively assess the collected ideas. Second, computerized text-based analyses of the submitted ideas were performed to examine textual features of the ideas and establish links between idea contributors' social behaviors and cognitive processes.

12.7.1.1 Expert Evaluation of Ideas and CA Facilitation

To allow an in-depth evaluation of the subject matter, the ideas and the utilized approach were assessed by four experts with different backgrounds of relevant experience in the domain of open innovation and ideation (see Table 2). Based on established idea evaluation dimensions in literature (Dean et al., 2006), we conducted semi-structured interviews via video call that lasted between 41 and 53 min. The interviews were conducted with an interview guide comprising open-ended questions. Questions about the general impression of the ideas and the approach of CA facilitation were followed by questions about the completeness, level of detail, comprehensibility, originality, acceptability, and relevance of the submitted ideas. Prior to the interviews, each expert was provided with context information regarding the conceptual approach, process, and topic, as well as a random subset of ten idea submission. The interviews were recorded and transcribed by paraphrasing and noting verbatim statements.

Table 2. Interviewees for evaluation of the idea generation approach and idea characteristics

Expert	Industry	Interviewee position	Professional experience	Gender
E1	Software	Business development manager	5-8 years	Male
E2	Real estate	Innovation project consultant	5-8 years	Male
E3	Mobility	Technology manager for innovation projects	2-4 years	Female
E4	Logistics	Startup software developer	> 8 years	Male

The experts understood the CA facilitator approach to gather external ideas and considered it useful, even if CA technology is currently applied for different use cases in their organization (i.e., all experts were familiar with CA technology). In particular, the dialogue-based interaction was judged to be promising to receive ideas from external contributors as part of an open innovation initiative ("It is easier for contributors, because you receive feedback from the CA."). Regarding the presented ideas, the experts emphasized the formulated ideas to be an extension of their own perspective. In this respect, some ideas particularly stood out, which were considered surprisingly unusual and novel (e.g., “I wouldn't have thought of such a thing.”). However, the experts noted that some ideas might be too radical from their point of view to be generally accepted. Nevertheless, one interviewee mentioned that radical approaches are a good sign, as they show an open process (e.g., “These are good food for thought and you don't want to see them stalled either.”).

The ideas were judged to be well elaborated and understandable. Regarding the level of detail, however, it was noted that even more idea-specific input would have been desirable. This would have allowed to go even deeper into the minds of the idea providers. It was suggested that the CA could have been even more proactive about specific terms used by the contributors, such as ridesharing, and asked specific questions (e.g., “What exactly do you mean by this?”). This would allow to obtain even more contextual knowledge. For example, the CA could also actively, i.e., without being addressed, have provided suitable suggestions from a database as an additional stimulus for the contributors to elaborate their idea (“It would be useful if there was a kick-start to trigger participation”). In relation to the assumed goal of the CA facilitation, i.e., collecting a large number of ideas, the experts mentioned that the ideas were already very well elaborated for a first idea collection step. “More detail is always possible, but it was enough for understanding” and an even more detailed level of elaboration could also complicate the idea screening and selection (e.g., “Who is meant to read through all that?”). Whether more content would be advantageous for a (partially) automated evaluation could not be conclusively assessed by the experts. The advantage of a more intensive dialogue should be weighed against the possible tendency of idea contributors to abort the process and a declining motivation to finish the idea generation (e.g., “They might get bored despite the engaging conversation at some point.”). Despite this, the experts expressed that the clear structure of ideas is certainly an advantage for the subsequent evaluation and selection, regardless of the method applied. Looking at the entire subset of ideas, the content was judged to be mostly consistent in terms of the different idea attributes. No obvious extreme deviations were noted by the interviewees.

When asked to what extent the provided ideas solve a problem in the context of the subject matter, it was stated that “the ideas address and comprehensively include the problem” and that very promising ideas had been proposed. However, further details would have been desirable and useful in some cases. Nevertheless, these ideas were a suitable starting point to identify one visionary idea among many in order to enter an in-depth exchange with this individual about his or her idea for solving the problem. Regarding the advantages of using a CA facilitator, the overall adaptability, and the possibility of accessing a current and large database that can be incorporated into the process of idea generation were highlighted. In the same context, the need for a large amount of data and its preparation for CA training was considered critical. One advantage that one expert emphasized was that a dialogical CA facilitation is suitable to involve all users regardless of their individual prerequisites, i.e., from a cognitive perspective, who can also have very useful ideas. In this regard, automatic adaptation of CA's behavior and utterances based on personal characteristics of the idea contributor was considered potentially valuable and could be leveraged with technological advances (e.g., "Especially when you think about the future possibilities that you don't want to miss, this is a great playground.").

12.7.1.2 Text-based Evaluation of Ideas

To link idea contributors' written language style in the gathered texts during the idea generation process to affective (e.g., negative and positive emotions) and cognitive processes (e.g., problem-solving), we conducted linguistic analyses with computerized text analysis. This form of text analysis has been used to study social networking sites, online discussion forums, group dynamics, and interactions between individuals (Kacewicz et al., 2014; Oliver et al., 2021; van Swol & Kane, 2019) and yields reliable psychological insights about individuals' thought processes, emotional states, intentions, and motivations (Boyd & Pennebaker, 2015; Tausczik & Pennebaker, 2010).

We examined the collected idea texts by applying a dictionary approach. We used the program Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015a, b). LIWC utilizes over 90 pre-defined categories, analyzes and classifies words within these categories, which allows for a consistent measurement of words, leading to concordant validity (Humphreys & Wang, 2018; Moore et al., 2021; Pilny et al., 2019). The fundamental power of the LIWC dictionary lies in the fact that it was thoroughly developed using established and standardized psychometric procedures that ensure external validity and high internal reliability (Boyd, 2017; Pennebaker et al., 2015a, b). Given the German text corpora, we rely on the translated German LIWC2015 dictionary (Meier et al., 2019), which captures an average of 83 percent of the words people use in written and spoken language.

To prepare the linguistic analysis, we followed the guidelines for German text samples to preprocess the texts before analysis (Meier et al., 2019). For the linguistic analysis (see Table 3), we use five general descriptive dimensions: word count (WC), words per idea (WPI), words per sentence (WPS), percent of words in the text that are longer than six letters (Sixltr), and percent of target words captured by the dictionary (Dic). In addition, we utilized four summary variables: analytical thinking (Analytic), clout, authenticity (Authentic), and emotional tone (Tone).

The four summary measures each reflect a 100-point scale ranging from 0 to 100 with standardized scores. The underlying complex algorithms are proprietary. The variables are constructed from various LIWC variables based on previous language research (Boyd & Pennebaker, 2015). The scale values reliably reflect the following psychological dimensions (Boyd & Pennebaker, 2015, pp. 21–22):

- **Analytical thinking**: a high number reflects formal, logical, and hierarchical thinking; lower numbers reflect more informal, personal, here-and-now, and narrative thinking.

- **Clout**: a high number suggests that the author is speaking from the perspective of high expertise and is confident; low Clout numbers suggest a more tentative, humble, even anxious style.
- **Authentic**: higher numbers are associated with a more honest, personal, and disclosing text; lower numbers suggest a more guarded, distanced form of discourse.
- **Emotional tone**: a high number is associated with a more positive, upbeat style; a low number reveals greater anxiety, sadness, or hostility. A number around 50 suggests either a lack of emotionality or different levels of ambivalence.

The level of analysis refers to the gathered texts during the idea generation process steps, i.e., idea text, elaboration questions (which problem is solved, idea novelty, target audience), and title, as these are sufficiently self-contained and distinct from each other to allow meaningful intra-process comparison. Keywords were not included, since the analysis of individual keywords based on the LIWC categories appears to make little sense. A total of 54 keywords, mostly one to two per idea and compound words (see explanation below), were assigned for identification purposes from the idea contributors. A single idea was submitted without any keyword.

Table 3. Results of the linguistic analysis of the submitted ideas

Segment	**WC**	**WPI**	**WPS**	**Sixltr (%)**	**Dic (%)**	**Analytic**	**Clout**	**Authentic**	**Tone**
Idea text	1295	32.38	15.42	35.98	79.31	97.06	68.78	33.31	83.54
Elaboration questions	1456	36.40	8.88	37.50	76.30	96.61	60.02	41.20	39.82
Title	133	3.33	3.80	54.14	54.89	99.00	69.14	57.71	88.32
Mean	961.33	24.04	9.37	42.54	70.17	97.56	65.98	44.07	70.56
SD	589.40	14.73	4.76	8.23	10.87	1.04	4.22	10.17	21.82
Grand mean [a]	5429.4	–	20.18	22.90	82.72	49.53	60.63	48.34	61.20
SD [a]	9245.24	–	119.94	4.15	6.93	20.62	14.86	24.41	27.69

SD = standard deviation. [a]Grand means and standard deviations stemmed from six text corpora according to Meier et al. (2019)

Although idea titles were relatively short on average (3.33 words per idea), they were included in the LIWC analysis because they are potentially informative covering a range from concise and descriptive to bold and lurid in a wording continuum. 54.14% of words in the title text were longer than six letters, which is notably higher than the respective percentages for the idea texts (35.98%) and question answers (37.50%). The result for the titles is related to the frequent utilization of compound words. Compound words consist of several nouns attached to each other and their extensive use is a peculiarity of the German language. While some of the most common compound words are included in the German LIWC dictionary, less common compound words are not recognized (Meier et al., 2019). This was reflected in the title texts with 54.89% of the target words identified.

The percentage of words longer than six letters were fairly at the same level regarding the idea texts and answers to the elaboration questions at 35.98% and 37.50%, indicating more active, i.e., less frequent use of long compound words, and consistent language across the process steps. Accordingly, the percentage of target words captured by the dictionary for the idea texts and answers were higher than for titles, at 79.31% and 76.30%, respectively. This puts them at about the same level as the fundamental German LIWC dictionary capture rate of 83%.

Considering the idea texts and the answers to the elaboration questions, the phrased sentences were almost one-half shorter at 15.42 to 8.88 words. This discrepancy is associated to the mixture of key phrases and rather short sentences in the answers to the questions. Remarkably, though, answers to the elaboration questions with 36.40 words per idea were longer than the idea texts with an average of 32.38 words. Thus, the elaboration questions contributed substantially to the overall idea generation process.

The idea texts, answers to questions, and titles are characterized by strong analytical thinking (opposed to narrative thinking) with each over 97-scale points. Accordingly, during the idea generation process, the idea contributors predominantly used a formal, categorical style of textual language that is associated with increased abstract thinking and a logical, complex way of cognitive processing. Individuals with such a predisposition in processing information tend to analyze, break down problems and are more likely to weigh facts (Boyd & Pennebaker, 2015; Pennebaker et al., 2014).

The texts of the ideas with 68.78 points and the titles with 69.14 points on the clout scale were almost on par. The answers to the questions were somewhat lower with 60.02 points. Compared to the grand mean clout score of 60.63 (*SD* = 14.86) points from the German LIWC dictionary (Meier et al., 2019), these scores reflect a somewhat greater level of contributors' competence and confidence in the text. In addition, individuals who score high on the clout dimension usually use more outward words and are more focused on the people they interact with than on themselves. This type of interaction has been found to be conducive in the context of online discussion forums supporting the type of interaction and engagement required to build knowledge (Adaji & Olakanmi, 2019; Kacewicz et al., 2014; Moore et al., 2021).

Authenticity scores for the text segments ranged from 33.31 (idea texts), and 41.20 (answers to elaboration questions, to 57.71 (title). Compared to the grand mean value of 48.34 (*SD* = 24.41) (Meier et al., 2019), the value for the idea texts was relatively low and the value for the titles was relatively high. In order to understand these values, it is helpful to look at base rates of word usage from which the grand mean was calculated. The data sets of "Expressive writing" (76.73 points) and German-speaking "Reddit" (35.09 points) formed the ends of the authenticity continuum. Reddit is a social media platform where individuals discuss and exchange ideas on various subject matters (e.g., sports, politics, and leisure) in the form of threads and forums. Expressive writing, on the other hand, comprised samples from cross-sectional and longitudinal studies in which individuals wrote about profoundly personal issues in stream of consciousness mode (Meier et al., 2019). This put the idea texts at about the same level as social media which reflects informal, netspeak language (Meier et al., 2019). Nevertheless, the relatively low values are related to a rather reserved and distanced form of communication.

Looking at the scale for emotional tone, it is noticeable that the answers to the elaboration questions reflected a lack of emotional terms (39.82 points). In comparison, the scores for the idea texts (83.54) and the titles (88.32) showed a rather high occurrence of positive verbal signs of emotion on the emotion scale, suggesting that the idea contributors were more emotionally involved during these steps in the idea generation process.

12.7.2 Evaluation of Idea Generation Process

To explore the phenomena of interest, namely engagement and social presence, we developed two animated mock-ups simulating the process of idea generation. We opted for the simulation of two context-based scenarios, as this allows us to obtain the necessary power for a statistical analysis, i.e., the required number of participants, in a resource-oriented manner. In these two independent simulations, one showed a person generating an idea being facilitated by the developed CA. The other simulation showed a person using a standard submission form. The latter serves as a control condition that corresponds to the conventional method for idea generation on idea platforms. The topic of the idea generation was presented to the participants and was identical to that of the open call ("Mobility of the Future") to perform the idea evaluation (see Sect. 7.1.). In both simulations the same idea was presented, which was obtained through the open call. Participants were informed about the research-only data processing and comprehensively introduced to the context of the study. Next, participants were randomly shown one mock-up simulation and asked to answer a subsequent questionnaire.

Participants were recruited through two platforms (i.e., poll-pool.com, prolific.co), enabling researchers to identify suitable participants while ensuring a diversified sample. The platforms allow participants to earn points by taking part in studies, which in turn can be passed on to participants in their own studies or can be redeemed monetarily. The platforms also ensure that surveys are conducted correctly, e.g., respondents who fall short of the median completion time are penalized or even excluded. This makes it more likely that participants will provide complete responses, rather than rushing the survey or completing it incorrectly. Moreover, prolific respondents tend to provide reliable data and prove to be more honest compared to participants from other platforms (Peer et al., 2017).

Nevertheless, we manually checked the data for discrepancies (i.e., very short completion times, identical and extreme answers), but did not have to disregard any subjects. To collect data, we utilized perceptual measures for engagement and social presence (see Appendix 1) in an ex-post survey. The questionnaire items for each construct were adapted from existing studies (i.e., Gefen & Straub, 2003; Webster & Ho, 1997), which have delivered reliable results before and have been modified for different contexts (e.g., Cyr et al., 2009;

O'Brien et al., 2018). The original wording was adjusted to cover the features of the subject in this study. All items were measured through a five-point Likert scale with response options from 1 (strongly disagree) to 5 (strongly agree).

A total of 221 participants answered the questionnaire. 115 participants (44.3% female, 55.7% male, mean age 29.24 years, $SD = 10.14$) responded to the CA condition. Of these, 13 participants had relevant experience with idea generation processes, 100 had none, and two did not respond. In the standard submission form condition, 106 participants (48.1% female, 51.9% male, mean age 29.6 years, $SD = 10.66$) answered the questionnaire. Of these participants, 18 had relevant experience with idea generation processes, 85 had none, and three did not answer this question.

After examining the data and frequencies of valid responses, the descriptive statistics were examined, i.e., inter-item correlations, medians, means, and standard deviations of scales (see Table 5). The reliability coefficients of the constructs were greater than 0.8, as measured by Cronbach's α, indicating a satisfactory internal consistency (Nunnally & Bernstein, 2008). The conducted graphical analysis and the Shapiro–Wilk test indicated that the data were not normally distributed. The correlation coefficients between variables for both conditions are displayed in Table 4. Negative correlations between engagement and gender $r = -0.22$, $p < 0.05$ and social presence and gender $r = -0.25$, $p < 0.01$ were found in the CA condition. Engagement and social presence were positively correlated in both conditions $r = 0.62$, $p < 0.01$ (CA), $r = 0.59$, $p < 0.01$ (standard submission form).

Table 4. Correlation coefficients between variables

Variable	Age	Gender	Experience	Engagement	Social Presence
Age	–	0.35**	-0.14[a]	-0.06	-0.03
Gender	0.32**	–	-0.25[a]*	-0.03	0.01
Experience	-0.09[b]	-0.14[b]	–	-0.03	-0.09
Engagement	-0.16	-0.22*	0.10	–	0.59**
Social Presence	-0.10	-0.25**	0.17	0.62**	–

Correlation coefficients of the CA condition ($N = 115$) are displayed below the diagonal and of the standard submission form ($N = 106$) above the diagonal. [a]$N = 103$. [b]$N = 113$. For gender: 1 = female, 2 = male. For experience: 1 = yes, 2 = no. *. $p < .05$; **. $p < .01$.

A Mann–Whitney-U-Test was calculated to determine if there were differences in engagement and perceived social presence between the conditions conversational agent and standard submission form (see Table 5). The test showed a statistically significant difference between both conditions in engagement $U = 3497.00$, Z -5.47, $p < 0.001$, $r = -0.37$, and perceived social presence $U = 2525.50$, $Z = -7.57$, $p < 0.001$, $r = -0.51$. The effect sizes of the difference between means can be considered as medium $|r| = 0.37$ and large $|r| = 0.51$ (Cohen, 1992).

Table 5. Descriptive and test statistics

	CA				Standard submission form					
Scale	*α*	*Median*	*Mean*	*SD*	*α*	*Median*	*Mean*	*SD*	*Mann-Whitney-U-Test*	*r*
Engagement	0.91	3.33	3.16	0.94	0.90	2.33	2.42	0.89	3497.00**	-0.37
Social Presence	0.91	2.60	2.66	1.01	0.88	1.50	1.64	0.66	2525.50**	-0.51

**p < 0.001.

12.8 Discussion

Organizations strive to leverage external knowledge and expertise by applying open innovation approaches to promote their innovation capability. To manage idea platforms for the outside-in process in such a way that prospective contributors are motivated and supported to voluntarily submit an idea and the large number of emerging ideas can be efficiently selected, we propose a design for a CA facilitated idea generation process. Building on the vast body of theoretical knowledge regarding the concept of facilitation, we derive design knowledge to determine purposeful characteristics and behavior of a CA facilitator. By evaluating the instantiated design knowledge in a dialog-based CA facilitator for idea generation, we provide results regarding the nature of ideas and characteristics of the process. The evaluation with knowledgeable experts and a computerized linguistic analysis revealed homogeneous idea contributions with a constant level of detail, a satisfactory level of comprehensibility, and a high analytical as well as logical character comprising outward-looking words. Furthermore, the questionnaire-based evaluation of idea generation process showed that CA facilitation induces a higher perceived engagement and social presence among contributors during the idea generation process compared to conventional form-based interfaces. In the following, we elaborate on the multifaceted implications of these findings.

First, the presented design demonstrates the integration of the facilitation concept into state-of-the-art CA technology. For this purpose, following Bostrom et al. (1993), we considered all facilitative acts to leverage support for idea contributors during task processing (task), for accomplishing associated goals (process), and to conduct a socio-emotional interaction. Thus, we integrate and extend previous approaches to CA facilitation, as these have so for examined different aspects in isolation such as supportive behavior for idea generation (Wang et al., 2007) and proactive prompting of desired behavior, e.g., the elaboration and reformulation of input (Louvet et al., 2017; Tegos et al., 2014, 2015). As the results of the evaluation of contributors' textual language style suggest that CA facilitation is related to a fact-based enrichment of information and that idea contributors are emotionally engaged and apply problem-solving and analytical thinking, we imply that CA facilitation may have a positive influence on idea generation in the context of open innovation. As a supplementary point, it should be noted that, in contrast to emotionality, the dimension of analytical thinking was consistent across all facilitative process steps. Consequently, linguistic analysis of the text data denotes that the idea contributors used analytical writing for idea text, albeit using a positive language style that suggests they were emotionally engaged. Under the given conditions, this can be associated with the CA's goal- and productivity-oriented behavioral capabilities. Furthermore, the data lends support to the finding that idea contributors were more focused on others than on themselves during the interaction when generating the idea text (Moore et al., 2021). This is a promising finding as it may indicate that humans focus on their interlocutor in this context, even when the partner is deliberately artificial but uses human language patterns.

Second, our results show that the idea generation process can be designed in such a way that idea contributors are more engaged compared to conventional form-based interfaces. This is a valuable insight in the context of open innovation processes (e.g., crowdsourcing, idea contests), as organizations struggle to motivate voluntary and unpaid idea contributors to start and complete submissions (Bretschneider, 2012). Besides manipulating the presentation of the task and goal (Benz et al., 2019; T. de Vreede et al., 2013), the implementation of a task-focused CA that facilitates the idea generation process in a human-like fashion constitutes an additional effective method to increase users' engagement. This insight is supported by the perception of the focus group participants who stated that CA facilitation reduced their initial hesitation to initiate the idea generation process and provided goal-oriented guidance in the process. In addition, the statistical analysis based on the survey following the simulated idea generation process has shown that significant differences exist between the CA facilitated and non-facilitated idea generation process in terms of engagement and perceived social presence. The fact that engagement and social presence correlate is not unexpected, as the concepts are closely linked. Interestingly, however, differences were observed between the two conditions with respect to significance in the correlations of the two constructs with the variable gender, which could be relevant for the further development of an individualized CA behavior.

Third, the generated design knowledge and design entity in the form of the CA facilitator provide a novel approach to enhance the efficiency of idea selection through an improved idea generation process. More specifically, supporting idea contributors reduces the likelihood of a heterogeneous pool of ideas with low levels of detail, elaboration, and likelihood of implementation. This idea generation approach provides organizations with the option to flexibly implement adjustments in the process and CA's facilitative acts to tailor the support of contributors to a specific task and determine a pre-defined set of required information. Accordingly, the facilitation of the idea generation process can serve as a preparatory step for a systematic idea selection process. Thereby, our findings address relevant questions about organizations' efficient management of large numbers of collected ideas with restricted resources in the context of open innovation initiatives (Blohm et al., 2013; Merz, 2018).

12.8.1 Contributions to Theory

Our results contribute to literature on CAs, collaboration, and open innovation. In terms of research on CAs, we provide a blueprint to implement the facilitation concept in CAs by considering all facilitative acts to achieve effective one-to-one support for individuals working on cognitively demanding tasks. In addition, we present an approach to elevate the level of user engagement by designing dialogues with micro and macro scripts that create a balanced division between task-focused and socio-emotional interaction. The results of our study also have implications for research on open innovation. The presented method for idea generation on idea platforms represents an approach to effectively involve and engage idea contributors. Therefore, CA facilitation is promising to serve as an additional mechanism to leverage user engagement and gather completed and elaborated submissions from voluntary contributors. With reference to collaboration research, this study contributes to investigations addressing the shift of static automated facilitation systems in accordance with the "Facilitator-in-a-Box" paradigm by Briggs et al. (2013) toward more pro-active, flexible, and intelligent conversation-based systems. More specifically, our results suggest that increasing the flexibility of support (e.g., answering questions about the task on demand) in a facilitated and structured process yields elevated conditions for individuals' task accomplishment.

By completing and communicating this DSR project, we present a nascent design theory of the type "design and action" (Gregor, 2006) with abstracted design knowledge in the form of four DPs. As this prescriptive design knowledge defines functioning and construction for the class of artifacts "conversational AI facilitation", it constitutes a mid-range theory that combines theoretical insights related to facilitation with solving a concrete problem through the implementation of an artifact (Kuechler & Vaishnavi, 2012). The abstractness and balanced projectability of the generated design knowledge allow its instantiation for similar artifacts (e.g., intelligent voice-based facilitation systems) in related domains (Vom Brocke et al., 2020). Therefore, the DPs can be reused to implement a related artifact in contexts where companies and institutions also depend on voluntary, substantive, and understandable textual descriptions of individuals' ideas and/or concerns. Accordingly, our insights can be utilized, inter alia, for customer service and citizen participation, to document customer requests or ideas from citizens and ensure an efficient subsequent processing of contributions.

12.8.2 Contribution to Practice

Furthermore, we contribute to practice by presenting a feasible and implementable concept for automated facilitation with CAs for the application on idea platforms as well as related domains with the goal of achieving more elaborate and detailed outcomes. The CA presented in this study can be adjusted and applied on idea platforms to facilitate individuals in the idea generation process. With this, the challenge of hardly scalable human facilitation on digital platforms can be overcome. Therefore, CA facilitation can support platform providers and organizations in managing the process of involving and engaging external idea contributors in their innovation processes. Thereby, organizations might increase voluntary participation by idea contributors, as the idea generation process is more appealing in comparison to standard submission forms. Moreover, for handling the large pool of submissions in outside-in open innovation processes, e.g., idea competitions or tournaments, the resulting structured and detailed submissions are beneficial to efficiently select promising ideas.

12.8.3 Limitations and Future Research

Despite the promising results, our study does not come without limitations. We acknowledge that simulating the idea generation process to evaluate user engagement and perceived social presence limits the conclusiveness of our results. Nevertheless, we chose this technique as part of our iterative DSR approach since it enabled us to achieve the necessary sample size to perform inferential statistical analyses. In addition, this approach allowed us to circumvent possible influences of NLP-related flaws on the results. In that regard, despite our efforts to base our CA facilitation on the best possible language model, in the preceding evaluation phase we discovered that in some cases the CA did not respond correctly to users' utterances, which may be reflected in the results but is not attributable to the facilitation concept as such. We are confident that the method of mock-up-based evaluation, which is widely used in interaction design research, meets the criteria to make a valuable contribution through statistically substantiated conclusions. To deepen insights on the effectiveness of the generated design knowledge, in future studies a CA facilitator should be implemented in an organization to analyze the impact on the operational efficiency in a longitudinal evaluation setting regarding the assessment and selection of external ideas. In addition, while we were able to measure engagement and social presence through the questionnaire, we did not examine how the participants perceived the facilitative support provided by the CA, e.g., regarding satisfaction with the idea generation process and its outcome. In this context, future research should examine how CA facilitation is subjectively perceived. In particular, it should be investigated to what extent the provided support by the CA is in line with needs of prospective idea contributors and explored what possible opportunities for adaptation exist. One promising avenue for future work in this context is to investigate the influence of flexibility during the facilitated idea generation by allowing contributors to choose the sequence of steps to produce creative ideas (Amabile et al., 2018). Finally, we based our text analysis on a proprietary algorithm to assess and interpret the characteristics of contributed idea texts. However, we are confident that the stated validity is accurate based on extensive previous language research and is applicable to our research with the understanding that text analysis is always context dependent. In future studies, computer linguistic text analysis should be used for evaluations to further the validation of this strategy in the realm of CA-based facilitation. Additionally, this approach could be adapted and applied to adjust the facilitation behavior of CAs to users. It is conceivable that, based on real-time analysis of input, users could be prompted by the CA to formulate their content differently (e.g., more analytically) to achieve desired outcomes.

12.9 Conclusion

As part of a multi-cycle DSR research project, this study presents a solution to elevate organizational idea generation processes on idea platforms with AI-based CA technology. While idea generation facilitation is critical to innovation, organizations struggle to leverage this potential on idea platforms. So far, large amounts of ambiguous, imprecise, and incomplete ideas hamper organizations in selecting ideas with potential for further processing. To address these challenges, we built on the facilitation concept to iteratively design and instantiate a scalable CA that facilitates individuals during their idea generation. Evaluation results suggest that the natural, dialog-based interaction encourages and engages idea contributors to provide clear, detailed, and complete ideas, which deliver a suitable grounding for the essential follow-up selection of textual ideas in organizations.

12.10 Appendix 1

Questionnaire Items and Sources.

Note: The questionnaire consisted of the following statements that were translated to German before.

Prior experience, one item, own formulation
Have you ever generated and submitted an idea for an external company or organization, i.e., that was not your own or for which you worked at the time? (Yes/No/I am not sure

Engagement, six items, adapted from Webster and Ho (1997)	
Attention focus	This interface keeps me totally absorbed in the idea generation.
	This interface holds my attention.
Curiosity	This interface excites my curiosity.
	This interface arouses my imagination.
Intrinsic interest	This interface is fun.
	This interface is intrinsically interesting.

Social Presence, five items, adapted from Gefen and Straub (2003)
There is a sense of human contact in the interface.
There is a sense of personalness in the interface.
There is a sense of sociability in the interface.
There is a sense of human warmth in the interface.
There is a sense of human sensitivity in the interface.

12.11 References

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13 May the Guide Be with You: CA-facilitated Information Elicitation to Prevent Service Failure

Poser, M., Hörhold, H. K., & Bittner, E. A. C. (2023). May the Guide Be with You: CA facilitated Information Elicitation to Prevent Service Failure. In *31st European Conference on Information Systems (ECIS),* Kristiansand, Norway.

Abstract

Companies automate the delivery of their online services by deploying artificial intelligence-based conversational agents (CAs). However, contemporary CAs still struggle to reliably answer the full range of requests from support seekers. To avoid service failure, service delivery activities of CAs and service employees should be interconnected by a handover of requests. This form of hybrid service delivery requires support seekers to disclose relevant information so that CAs can relay them to service employees prior to an imminent failure. By integrating and extending design knowledge from two DSR projects, we derive four design principles (DPs) to prepare handovers. These DPs guided the implementation of a service script in a CA prototype to facilitate the elicitation of information from support seekers. Based on two evaluation episodes, we show that support seekers feel supported by the CA in disclosing information which results in elaborate input for subsequent processing by service employees after handover.

Keywords: Hybrid Service Delivery, Conversational Agent, Handover, Facilitation.

13.1 Introduction

Organizations are increasingly leveraging the capabilities of artificial intelligence (AI) to automate business operation processes (e.g., candidate selection, financial fraud detection, and prevention) (Ghosh et al., 2019). With its evolving technological foundations, such as machine learning (ML), AI technology is increasingly able to autonomously perform cognitive tasks in knowledge and service work that demand information processing capabilities (e.g., deductive analytical behavior) (Huang and Rust, 2021). Thereby, the application of AI offers companies the potential to increase their business value (Coombs et al., 2020; Lacity and Willcocks, 2021).

Due to its data richness, especially online service delivery represents a prominent application context for AI. With a continuously growing volume of requests, organizations are exploiting the current capabilities of AI to deliver faster and more efficient service within or across company boundaries to support seekers such as customers or employees (Larivière et al., 2017; Davenport and Ronanki, 2018). This trend of AI-based request handling is predicted to grow to a 95% share by 2025 (Servion, 2018). Seeking to provide elevated service quality for support seekers in these encounters (Mero, 2018), companies are transforming their text-based online service delivery. Therefore, they are adopting AI-based self-service technology that is capable of individualizing service interactions (Larivière et al., 2017). In this context, conversational agents (CAs) have gained popularity, as they allow a human-like, intuitive, and personalized dialog-based interaction with support seekers. Hence, CAs are frequently implemented to automate the processing of knowledge-intensive service requests across various work contexts (e.g., customer service, IT support) that have previously been performed by service employees. Thereby, companies can offer service at any time to quickly resolve support seekers' requests (Thorne, 2017; Fiore et al., 2019; Verhagen et al., 2014).

Nevertheless, AI-based CAs are still far away from achieving human intelligence which causes difficulties in processing complex requests and leads to the provision of unsuitable information (Statista, 2019; Li et al., 2020). Due to these service failures, companies are unable to deliver desired outcomes (Smith et al., 1999). Consequently, support seekers' satisfaction with the service delivery process and acceptance of a CA can get jeopardized. As Seeger and Heinzl (2021) reported, there is a high prevalence of these CA failures in practice which is reflected in a vast number of white papers on the internet addressing this issue and its consequences for companies (Bowers, 2019; Walby, 2022). To alleviate these negative effects and perpetuate CA acceptance among support seekers, initial research is investigating service recovery strategies. One research stream addresses automated conversational repair approaches by focusing on different forms of recovery through interaction between CA and support seeker (Reinkemeier and Gnewuch, 2022; Følstad and Taylor, 2020). These repair attempts include CA actions such as conveying messages that prepare users for failure, prompting users to paraphrase their input or select from provided options to continue the dialog (Weiler et al., 2022; Benner et al., 2021).

In addition to these automated approaches, service recovery strategies are needed that include fallbacks to service employees. Thereby, service failure can be prevented if CA-controlled repair attempts have repeatedly failed (Schuetzler et al., 2021; Benner et al., 2021; Poser et al., 2021). This requires the redesign of service processes to integrate existing work practices of CAs and service employees (Vassilakopoulou et al., 2022; Poser and Bittner, 2021). For continued request processing, either connected or disconnected service process steps can be established. For this purpose, handovers are used where requests of support seekers are relayed from the CA to the service employee for further processing. With connected processes, a request can be immediately handed over to the service employee and seamlessly handled (i.e., by entering the same chat). Disconnected processes imply a time delay in request processing by the service employee (i.e., request sent as a ticket) (Poser et al., 2022c). However, for any service recovery that involves the handover of a request to the service employee, suitable information needs to be available.

Until now, however, there is a knowledge gap on how to ensure the elicitation of elaborate information to prepare a potential handover to service employees (Poser et al., 2022a; Poser et al., 2021). To do so, on the one hand, support seekers should be supported in providing relevant and detailed input during encounters. On the other hand, the collected information should meet the requirements of service employees to assist them during request processing after the handover. To address these aspects, the capabilities of CAs can be used to provide structural guidance and assist seekers in a flexible and human-like dialog. By providing an engaging interaction with on-demand support and feedback, service seekers' problems (e.g., comprehension questions) can be reduced and the documentation of information can be improved. For the creation of this dialog, we utilize service scripts that define procedures and activities for specific situations during customer encounters (Kirsch, 1996; Sands et al., 2021). Furthermore, we draw on the concept of facilitation to structure the dyadic interaction with CAs for this well-defined and repetitive task (Tavanapour et al., 2019; Clawson et al., 1993). Thereby, we aim to create a service script for CAs that allows the elicitation of information required by service employees to process requests after handover. Accordingly, we pose the following two-part research question: *How should a CA be designed to (I) assist support seekers in disclosing information (II) that can help service employees in processing requests after handover?*

To address this research question in the context of text-based online service delivery, we investigate intra-company IT support as a prominent internal work context for companies to pilot AI-based technology. Following the design science research (DSR) approach (Hevner et al., 2004), we present prescriptive design knowledge to structure the interaction between support seeker and CA to prepare potential handovers. Therefore, we draw on existing design knowledge from the knowledge base and complement it with problem-motivated design aspects derived from the application domain. The remainder of the paper proceeds as follows. In Section 2, we present related work on AI-based online service delivery, IT support, and CAs. Next, we delineate our research approach in Section 3. Subsequently, we identify objectives of a solution in Section 4, derive the design in Section 5, and demonstrate and evaluate the design in Section 6. We finish our paper with a discussion and conclusion in Sections 7 and 8.

13.2 Research Background

13.2.1 AI-based Online Service Delivery

Companies are progressively delivering intangible services online to meet support seekers' increased demands for convenient and fast resolution of requests that concern their needs (e.g., consultancy) or state of objects (e.g., product troubleshooting). To do so, online channels are used to offer support seekers support through self-service (e.g., web portals) or service employees (e.g., chat, email). This allows companies to effectively deliver information-rich and time-critical service with a utilitarian and relational nature (Froehle, 2006; Barrett et al., 2015). With the objective of enhancing the accessibility of these online-based service offerings and simultaneously ensuring operational efficiency and satisfactory service experience, AI-based self-service solutions are increasingly deployed (Huang and Rust, 2021). Offering the potential to create value in service environments, AI is defined as the ability of systems to interpret data input, execute actions, make decisions, and learn (Manser Payne et al., 2021; Haenlein and Kaplan, 2019; Bock et al., 2020). For online service delivery, AI appears predominantly in two forms: AI-based agents (e.g., CAs) are represented with a virtual identity and allow interaction via natural language; embedded AI is integrated into systems or applications with different interfaces (Glikson and Woolley, 2020; Poser et al., 2022c).

Recently, research has shown that the range of service tasks that can be executed by AI has expanded as its capabilities have evolved (Huang and Rust, 2018). More specifically, insights from research and practice demonstrate that AI is currently capable of autonomously processing homogeneous, repetitive, well-defined, and knowledge-intensive requests in encounters with support seekers (Zierau et al., 2020; Coombs et al., 2020). However, contemporary AI is so far unable to handle non-routine requests that require experimentation and intuitive processing (Schuetzler et al., 2021). To leverage the potential of AI-generated value, different deployment scenarios for online encounters with support seekers have been proposed and studied. On the one hand, AI-performed encounters refer to AI autonomously co-creating service with support seekers. On the other hand, AI can augment encounters between support seeker and service employee visibly or invisibly (Ostrom et al., 2019; Keyser et al., 2019). In this vein, the design of CAs' representation and interaction with support seekers has been extensively studied to positively affect the service experience (Zierau et al., 2020). To augment service employees during encounters with support seekers, initial research focuses on dashboards (Dubey et al., 2020) or CAs (Gao and Jiang, 2021).

As online service tasks are interdependent and AI still regularly fails in processing complex requests, hybrid forms of service delivery involving both AI and service employees are increasingly explored (Ostrom et al., 2019). As a result, new tasks arise for service employees to deliver service, such as monitoring and rectifying AI failure (Coombs et al., 2020). So far, however, there is a lack of knowledge about the interrelationships between service employee, support seeker, and AI as well as about the division and linkage of (sub-)tasks between service employee and AI allowing hybrid service delivery (Bock et al., 2020).

13.2.2 IT Support and AI

A prevalent work context for deploying AI-based online service delivery is IT support. This intangible service includes maintenance, problem-solving, and consulting on IT products (hard- and software) that were sold to external customers or are deployed in an organization (Shaw et al., 2002; Poser and Bittner, 2021). Accordingly, service offerings are directed toward internal or external support seekers. In this context, service employees are responsible for providing immediate, efficient, and high-quality support to support seekers, ensuring error-free use of IT products (González et al., 2005). Thus, questions are answered, assistance is provided with the installation of soft-and hardware, and problems are solved. In order to handle the varying degrees of complexity and problems, the IT support process is organized hierarchically (Marrone and Kolbe, 2011). In first-level support, requests or problems are accepted via various communication channels with the aim of finding solutions quickly. If the request cannot be resolved, a ticket will be created and escalated to a higher support level. Second-level support then provides direct support or offers solution approaches for more complex requests or problems. Third-level support handles tickets that require an individual solution through customizing the IT product or service (Simoudis, 1992).

The number of requests and their diversity in content is increasing in IT support, causing high demands on service employees (Poser and Bittner, 2021). Hence, to ensure timely and efficient restoration of IT operations, AI-based systems are investigated and used to automate or augment (sub-)tasks for service delivery (Crowston and Bolici, 2019). For instance, CAs can tackle the large volume of requests in first-level support as a self-service channel for support seekers (Fiore et al., 2019; Schmidt et al., 2021). In this context, research shows that CAs can answer FAQs and autonomously solve a restricted set of problems of support seekers (Meyer von Wolff et al., 2020; Vinyals and Le, 2015). In addition, embedded AI applications are studied to support service employees by providing suitable knowledge during request processing (e.g., Graef et al., 2021). However, as of yet, AI has often been deployed and studied as a stand-alone solution solving only a subset of issues. The interconnectedness between AI and service employees to achieve a purposeful integration of AI across service delivery activities has not yet been addressed. Furthermore, the perspective of service employees in AI-based service delivery has not been considered much (Poser and Bittner, 2021).

13.2.3 Conversational Agents

CAs represent AI-based agents and are defined as software systems that interact with users via natural language (Diederich et al., 2022; Bittner et al., 2019). Depending on the interaction mode (text vs. speech) and appearance (virtual identity vs. no identity), different terms such as chatbot, cognitive assistant, virtual or personal assistant are used to refer to CAs (Gnewuch et al., 2017). Due to their ability to communicate in a human-like manner and conduct personalized interactions, CAs are used in various domains for service-related tasks (e.g., finance, education, customer service, IT support) (Keyser et al., 2019). Their intuitive use facilitates unobstructed interaction and elevates the accessibility of online service offerings (Adam et al., 2021a). As CAs are capable to capture and retrieve knowledge as well as execute or trigger actions in systems, they are frequently used for automated, text-based self-service encounters with support seekers (Meyer von Wolff et al., 2019). In order to improve the adoption, use, and usability of CAs, different aspects have been investigated in research (Lewandowski et al., 2023). One stream of research examines the influence of social cues in terms of representational features (e.g., gender) and interaction style (e.g., message length, service scripts) on users (Sheehan et al., 2020; Sands et al., 2021). Another stream addresses technical characteristics to sustain error-free usage (natural language processing (NLP) engine, response latency) (Edirisooriya et al., 2019; Hu et al., 2018).

Despite the advances in ML and NLP, CAs still cause conversational breakdowns (Benner et al., 2021). To prevent these CA failures, research endeavors explore repair strategies and their effects on support seekers (Huang and Dootson, 2022). In this context, approaches of automated CA-initiated repair strategies are pursued that incorporate, among others, the detection of the error type and the application of suitable actions (Reinkemeier and Gnewuch, 2022). In addition, hybrid repair strategies with fallback to service employees are investigated. For this purpose, handover scenarios are considered in which CAs relay requests to service employees when previous automated CA-initiated attempts have failed. For these service recovery strategies, requests from support seekers are handed over and either resolved directly or delayed. In previous research, the perspective of support seekers during handover (Wintersberger et al., 2020), the procedural flow and the information categories required for service employees have been examined (Poser et al., 2021; Poser et al., 2022a). So far, however, there is a lack of knowledge on how CAs can gather relevant information in the interaction with support seekers to prepare a handover and thereby support service employees' subsequent request processing.

For the design of CA-guided service encounters, service scripts have been introduced to define CAs' activities and their sequence for different interaction scenarios (Sands et al., 2021). Hence, service scripts can be used to define the behavior of CAs for the elicitation of information. To define these activities, the concept of facilitation can be applied, which focuses on supporting individuals to achieve a task goal through interventions in a structured process (Clawson and Bostrom, 1996; Clawson et al., 1993). In the established facilitation framework of Bostrom et al. (1993), the activities for automated facilitation refer to (1) process and (2) relationship aspects to sustain (3) task achievement. Previous research has examined CA facilitators in various contexts. The results illustrate that CAs are capable of guiding individuals through a task process (Tavanapour et al., 2019), prompting for input or reformulation of input (Louvet et al., 2017), and providing task-related support (Wang et al., 2007). Accordingly, the concept of facilitation could be used to engage support seekers in a process of information elicitation to prepare a handover to service employees and thereby address the described research gap.

13.3 Research Approach

In this paper, we adopt the DSR paradigm to produce a solution for a prevalent real-world problem in online service contexts that are characterized by a lacking interconnectedness of activities performed by AI-based CAs and service employees (Hevner et al., 2004). To derive a CA design that sustains hybrid service delivery via handovers, we use the interior mode of DSR (Adam et al., 2021b). Accordingly, we create and evaluate prescriptive design knowledge and demonstrate a designed CA artifact.

To overcome the commonly limited reusability of design knowledge and minimize its monolithic structure, we create and evolve design knowledge across two DSR projects (see Figure 1) (vom Brocke et al., 2020; Baskerville and Pries-Heje, 2019). Initialized by the identification of a shared problem, we aim to produce suitable design knowledge that, due to its projectability, is applicable to a class of problems for related application domains. More precisely, we derive design principles (DPs) by iteratively performing design cycles across two projects to enable consecutive task processing involving the handover from a CA to an employee in semi-automated task settings. By accommodating for CAs' bounded capabilities, we aim to ensure that their preceding activities support subsequent human task accomplishment. The solution development revolves around a human-centered documentation process of user input (e.g., concern, problem, feedback) by a CA to support users and enable employees to finish a task after handover.

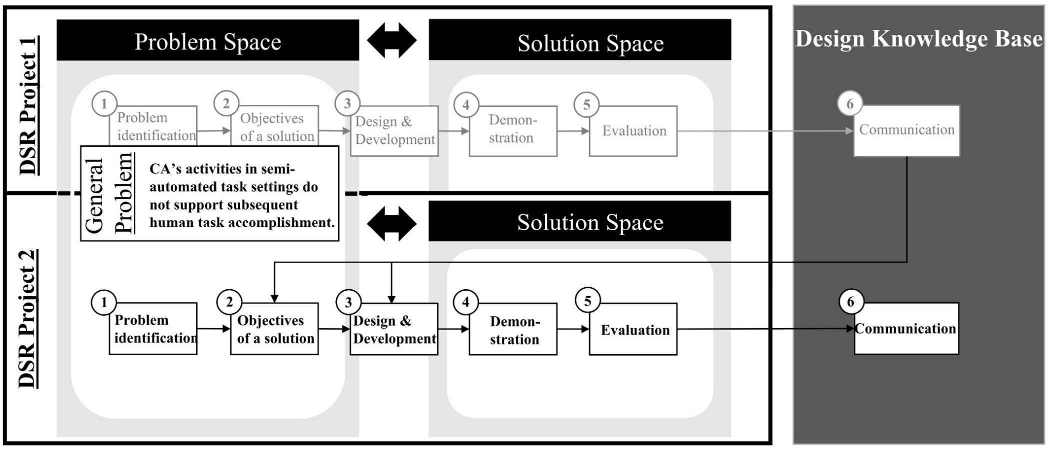

Figure 1. Interconnection of DSR projects structured with DSRM.

For the DSR project covered in this paper, we initialized the six-step DSR method (DSRM) by Peffers et al. (2007), to address missing CA's activities and handovers of information to support service employees' subsequent task accomplishment in IT support (**Problem Identification**). In search for **Objectives of a Solution**, we identified a preceding DSR project that addressed a related problem. In DSR Project 1, we generated design knowledge to support users in providing elaborate and detailed input through a CA facilitator in the context of crowdsourcing (Poser et al., 2022b). The evaluation of this design knowledge indicated that the quality of information handed over to employees sustained their subsequent task processing. As the DPs from DSR Project 1 are characterized by a high projectability with moderate abstractness and high concept density (Wache et al., 2022), we considered them to inform the solution development in DSR Project 2. To ensure their fitness, we derived practice-oriented meta-requirements (MRs) from the application domain IT support. Therefore, we conducted semi-structured interviews with six experts

(E1-6; gender: three female, three male; work experience: 1-20 year(s); fields of expertise: first-level, second-level IT support, quality assurance, development) from IT support to gain insights into the (1) nature of information in service tickets and (2) problems support seekers face during submission of requests. Based on verbatim transcripts, we performed a qualitative content analysis following Mayring (2015) that delivered issues to formulate MRs defining characteristics of a CA capable to elicit relevant information from support seekers (see Section 4). For the analysis, in the first step, the research team inductively developed code categories. Based on 30% of the verbatim transcripts, these categories were defined, subsumed, and grouped into main categories. In the second step, the remaining transcripts were analyzed and adjustments were made to code categories. In this open coding process, the researchers generated categories that were continuously harmonized to avoid researcher bias (e.g., confirmation bias). As a result, 5 main categories and 12 sub-categories emerged. For **Design and Development**, we enriched the existing DPs from the previous DSR project with the newly derived MRs in order to define a final set of DPs. Based on these updated DPs, we specified design features (DFs) to guide the development of a CA prototype, which was created with Botpress[1]. To construct this prototype, we created a training dataset based on a ticket sample drawn from the pool of a cooperating organization that processes IT support tickets in the field of public transportation (see Section 5). Subsequently, as a **Demonstration**, the CA was tested by 15 participants in a user test (see Section 6.1). To evaluate the applicability and feasibility of the design knowledge as well as the effects of the CA on support seekers, a quantitative questionnaire was administered to the participants. First, the instantiated DPs were assessed with five items (e.g., "How helpful are the guidance and suggestions of the CA?"). Second, 18 standardized items were included from the scale 'user satisfaction with question answering systems' by Ong et al. (2009) comprising subscales on ease of use, usefulness, service quality, and information quality. All items were rated with a 5-point Likert scale. In the **Evaluation**, we examined the effectiveness of the CA by analyzing the elicited information after the handover. For this purpose, four experts (E1-4) from the second step (Objectives of a Solution) individually reviewed information from current tickets and information elicited by the CA. To evaluate the level of detail, completeness, comprehensibility, specificity, and processability, experts were interviewed. We used the verbatim transcripts to perform a qualitative content analysis (Mayring, 2015) (see Section 6.2). According to a deductive procedure, we formed three ordinal categories (quality, meaningfulness, and processability/processing) and two nominal categories (advantages/disadvantages and improvements in quality) based on the question categories from the interview guideline. **Communication** will be completed with the publication of this paper.

[1]https://botpress.com/download

13.4 Objectives of a Solution

To derive a solution and basic goals for the design, MRs were defined by incorporating the perspectives of service employees and prospective support seekers to identify relevant design aspects for the CA, prevent existing challenges, and ensure the elicitation of relevant information. Based on adverse characteristics of information of current tickets that refer to incorrect or incomprehensible as well as missing information, information elicitation by a CA should be determined.

Tickets are often not complete and lack details: "Not enough information is available in a well-prepared form" (*E4*). In addition, the required information about the problem description is missing (e.g., an error message). "In some cases, the description is only two lines of text" (*E2*). (**Issue1.1**). Moreover, associated data that helps service employees to grasp the underlying issue of the request (e.g., screenshots or personal data of the support seeker) is often unavailable. As a result, "90% of the tickets are incomplete" (*E5*) (**Issue1.2**). These shortcomings in content, incorrect, or missing information occur "because customers can write freely" (*E1*). Support seekers "often do not adhere to predefined guidelines, do it the way they think it should be done" (*E2*). Therefore, a guiding structure incorporating requests for required information would be useful (**MR1.1**). In addition, obligatory information for request processing should be defined because "tickets are better with mandatory fields" (*E5*) and the submission of requests without this information should not be accepted (**MR1.2**).

MR1: The CA should point users to mandatory fields and record the input.

As support seekers supply insufficient or incomplete content in their requests, service employees are required "[…] to repeatedly ask for information" (*E2*), which is time-consuming (**Issue2.1**). "Asking again - one to three times on average - because of incomprehensible information is most time-consuming" (*E6*). Explaining to support seekers what information is needed demands a high level of communication effort for service employees. During these contacts, service employees have to "[…] pose specific questions to get what you need" (*E2*). Apart from the time invested in communicating with support seekers, additional workload is caused by "correcting tickets which involves multiple feedback iterations" (*E4*) (**Issue2.2**) and requires changes in ticket documentation. In this context, "ticket correction is not complicated, just time-consuming" (*E2*) (**Issue2.3**). Additionally complicating the ticket processing is delayed response times of support seekers. This results in "additional work time between 5 and 30 minutes, up to hours or days" (*E6*), which can hinder the final closure of tickets for a long time (**Issue2.4**). As shortcomings in content or missing information arise because support seekers "sometimes do not realize the importance of information items" (*E4*) or "forget to follow guidelines" (*E3*), support seekers should be supported in submitting complete and comprehensive input. This requires a standardized process comprising a "concrete list of questions" (*E2*)

(**MR2.1**). support seekers should understand that it is necessary to follow the process. "If customers are guided step by step, you get what you need" (*E1*) (**MR2.2**).

MR2: The CA should present and guide through a followable process by asking relevant questions step by step.

Furthermore, support seekers have difficulties summarizing appropriate content due to comprehension problems or lack of knowledge: support seekers "[...] write what they know" (*E6*) (**Issue3.1**). Accordingly, support seekers regularly - despite specifications of desired content - do not know what is needed or are not aware of the importance of certain information (e.g., content is generic). Hence, for service employees "it is usually not clear what is meant" (*E2*) (**Issue3.2**). In addition, some support seekers formulate multiple concerns into one request at the same time (**Issue3.3**). Overall, the quality of the provided information depends on the experience of the support seekers. Individuals "with whom you have a lot of contact create better tickets" (*E1*) than those with whom IT support rarely has contact. Hence, during information disclosure, the theme of a request should be identified to guide support seekers through a specific process, as "well-directed questions make it easier for individuals" (*E1*) (**MR3.1**). In addition to specific questions in the process, assistance should be offered when support seekers do not know what is required or have questions (e.g., explanation of prompted information items). Accordingly, to prevent support seekers from feeling helpless, suggestions should be made for specific questions (**MR3.2**).

MR3: The CA should understand and categorize requests to ask appropriate questions and provide explanations and suggestions when users have difficulties in understanding.

Generally, support seekers experience distress before submitting a request and wish for an individualized and appeasing interaction. Therefore, a CA should give support seekers the feeling that he or she is being helped. More specifically, "individuals need to feel that their request is being taken care of" (*E6*) (**MR4.1**). In addition, the CA should conduct a personal, friendly, and intuitive interaction with support seekers (e.g., provide button-based response options). In doing so, the CA should be empathetic and support seekers "should not feel dumb" (*E4*) (**MR4.2**).

MR4: The CA should conduct a friendly, intuitive, and empathetic interaction with users.

13.5 Design and Development

In this section, we present DPs of the type form and function from two DSR projects. In addition, we illustrate and describe the instantiation of the DPs with a situated implementation in form of a technical prototype.

13.5.1 Design Principles

We utilize the facilitation framework of Bostrom et al. (1993) to categorize CA capabilities and activities according to aspects of process, task, and relationship. In the first DSR project, we created four DPs (DP1.1-1.4) to design CAs that are able to guide users through a process to disclose information in a structured way (Poser et al., 2022b). To complement this design knowledge, we defined two additional DPs (DP2.1-2.2) based on the practice-oriented MRs from the second DSR project. Finally, following a supportive approach, we integrated an (re)defined the DPs (see Figure 2).

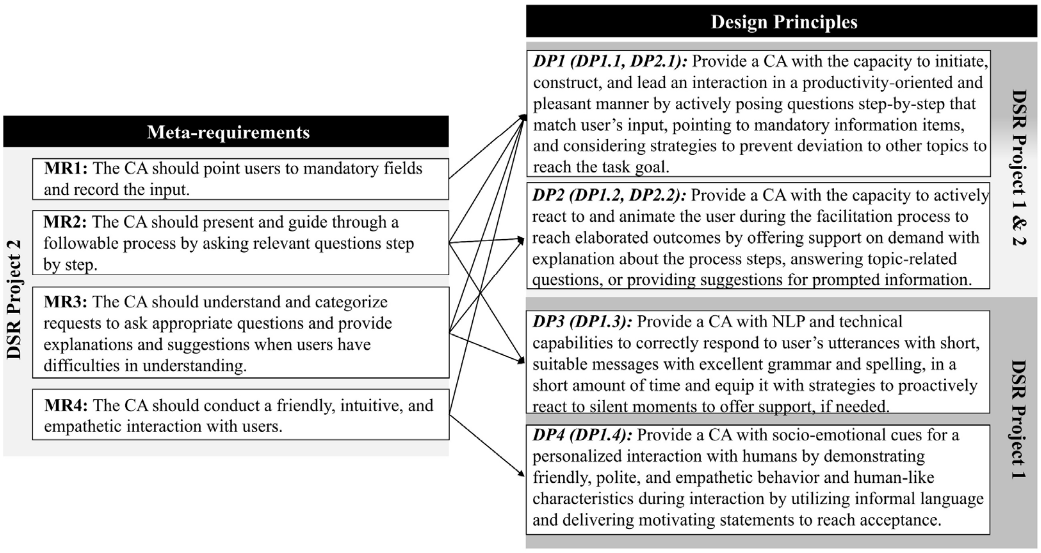

Figure 2. MRs from the current DSR project and DPs from both projects.

Process and task. Facilitative activities related to process and task are intended to inform and instruct individuals about the task. For this purpose, the CA should be able to initiate a dialog, explain the task at hand with its relevant steps, and guide support seekers through the process in a productivity-oriented fashion to elicit relevant information by asking questions (**DP1.1**). To be able to record different types of information, the CA should be able to guide through different processes based on users' input, pose matching questions, and point out mandatory information items (**DP2.1**). During this process, the CA should respond to the support seeker, motivate him or her, offer help with process steps, answer input-related questions, and provide explanations (**DP1.2)** as well as suggestions for prompted information to receive detailed and elaborate input (**DP2.2**). In general, for the CA to be able to guide the support seeker through a process to elicit information, the support seeker's intentions should be correctly recognized and responded to quickly with predefined messages (**DP1.3**).

Relationship. Creating a pleasant atmosphere during the process of information elicitation is important. In this regard, support seekers should feel that they are taken seriously. Therefore, the CA should offer personalized and friendly interactions and provide socio-emotional support (**DP1.4**).

13.5.2 Instantiation

The CA prototype was created using Botpress and made accessible for evaluation via a website embedded in a chat window. We used the Botpress NLP engine to train the ML model with information from existing tickets. For the evaluation of the instantiated design, the inclusion of tickets was limited to error messages for three common thematic categories extracted from a representative sample of tickets from the collaborating organization's ticket pool. The development of the CA prototype entailed the definition of a service script to outline the basic conversation flow during information elicitation (see Figure 3). To define the activities of the CA, we used the Botpress dialog manager. Furthermore, we defined the representation and interaction style with dialog texts (see Figure 3 for dialog snippets). To guide the development of the prototype, based on the DPs we derived the following DFs.

To proactively initiate the elicitation of information, the CA offers user buttons to determine the superordinate category of support seekers' requests and subsequently pose questions (**DF1**: *DP1, DP2*). To inform users about relevant and required information, the CA describes items before prompting the support seeker to disclose them and displays a summary of documented input before handing it over to the service employee (**DF2**: *DP1, DP2*). An appropriate subcategory is recognized based on user input and a corresponding dialog is triggered and suitable questions are posed (**DF3**: *DP3, DP1*). During information elicitation, the CA should proactively offer and provide examples of what appropriate information looks like for the requested information items (**DF4**: *DP2*). To create a pleasant user experience, the CA should be represented by an avatar and address users directly in a friendly and respectable way (**DF5**: *DP4*).

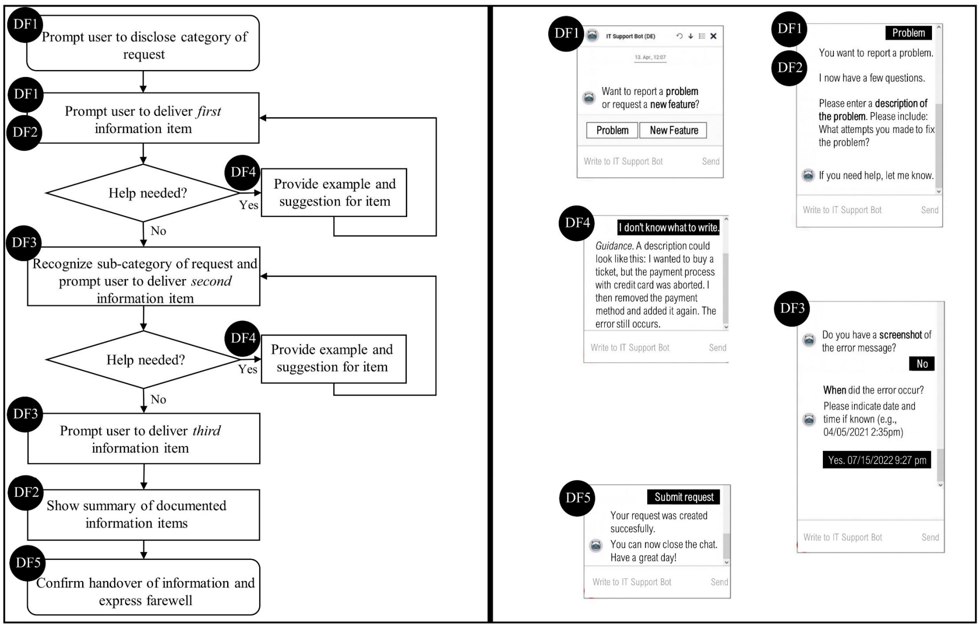

Figure 3. Service script (left) and exemplary snippets (right – translated into English) of the information elicitation with corresponding DFs.

13.6 Demonstration and Evaluation

This section presents two evaluation episodes to assess the instantiated design knowledge and support seekers' satisfaction with the CA. In addition, the suitability of information that was elicited with the help of the CA for subsequent processing by service employees is determined.

13.6.1 Demonstration

As part of the demonstration, we evaluated the materialized DPs and performed a user test to assess support seekers' experience with the CA during the process of information elicitation. To do so, 15 individuals, consisting of service employees from the collaborating organization and potential support seekers, each submitted a request and disclosed information using the implemented CA. This user test was based on a simulation, as participants submitted a request after they were given detailed background information on various regularly submitted errors. To perform the user test, participants were given access to the web-based CA. The ticket submission process could be started by the participants themselves. After submission, participants were asked to complete a quantitative questionnaire.

To gain insights into the implementation of the DPs, five questions were answered and received good to excellent ratings. This result illustrates the successful instantiation, applicability, and feasibility of the DPs. More specifically, the elicitation of information to submit a request was rated as satisfactory (M = 4.40, Mdn = 5.00, SD = 0.71). Participants perceived the offered assistance and proposed suggestions for information items by the CA as supportive (M = 4.00, Mdn = 4.00 SD = 0.89). During the interaction, participants felt well informed to enter the information requested (M = 4.47, Mdn = 5.00, SD = 0.71). In addition, the CA was rated as respectful in personality (M = 4.47, Mdn = 5.00 SD = 0.71) with an appropriate level of direct and personal interaction (M =4.20, Mdn = 4.00, SD = 0.74).

Complementing these findings, results from the user satisfaction questionnaire indicate that participants were generally satisfied with the CA-guided information elicitation process (see Table 1). The *ease of use* and *usefulness* ratings imply that the CA was user-friendly and has the potential to increase the effectiveness and productivity of submitting a request. The information presented during the interaction (*information quality*) was rated as relevant, and understandable but not tailored to the individual user. In addition, the CA was rated to provide a high quality of service, as it operates reliably and quickly.

Table 1. User satisfaction results.

Scale	No. of items	Mean (Median)	SD
Ease of use	5	4.36 (5.00)	0.23
Usefulness	5	4.20 (4.00)	0.07
Service quality	4	4.40 (5.00)	0.12
Information quality	4	4.35 (5.00)	0.31

13.6.2 Evaluation

For the evaluation, we examined the information generated by participants in the previous evaluation episode (see Section 6.1) during the CA-facilitated elicitation process to verify the effectiveness of the CA prototype. For this purpose, four experts each reviewed information from current tickets and compared it with information elicited by the CA for the same request category.

The *level of detail* of information obtained by the CA during the process "is more detailed, as it checks whether everything has been entered" (*E1*). Relevant information is attained through proactive prompts by the CA which sustains the "immediate recognition of the issue the user is facing" (*E2*). In addition, the "level of detail is optimized by omitting unimportant elements" (*E4*). In terms of *completeness*, the obligation to provide information results in a higher volume of information that is required by service employees than in current tickets: "the user cannot get around it and has to provide the information via the CA, so it is definitely more complete" (*E1*). As a result, "you have a better understanding of the request […]" (*E3*). Moreover, "by specifying what kind of information we need via the CA, users provide us with more or almost all information we need" (*E2*). The *comprehensibility* of the information is "[...] higher compared to current tickets" (*E3*) and "[…] you see directly: this is the problem, this is what happened" (*E2*). A request-based collection of information leads to thematically related items, which sustains service employees' recognition of requests. In this context, the information handed over by the CA support service employees, for example, "the categorization in the title is very good in content" (*E3*). "If you hold individuals by the hand and tell them I want to know this and that, then information is directly more comprehensible for us" (*E1*). In general, there is an improvement in terms of clarity and quality of information elicited by the CA as support seekers have to understand step by step in the process what their request is about. Regarding *specificity*, the information obtained by the CA covers the relevant items. The proposed help and suggestions reduce ambiguity in the content. "It's the specificity that's helpful because users have to keep input short. Of course, they can write extensive texts, but very few people will do that with a CA" (*E2*).

The characteristics of information obtained by the CA have an impact on their subsequent processing by service employees. "At best, you have all information at a glance and can start right away" (*E1*). The processing improves because the "[…] overview and categorization are clearer and predominantly relevant information reduced to the most important items can be identified more quickly" (*E4*). Overall, "the work is more on the user to tell us what the problem is, not on us to figure it out" (*E2*). This can shorten the processing time, as "the user enters everything via the CA, ideally, it all fits and you have the information and start working" (*E2*) - this reduces feedback loops. The handover to service employees "[…] speeds up the entire workflow considerably, which can save employees' time" (*E2*) as information is categorized with a title and description.

Despite these positive aspects in terms of information characteristics, there is potential for improvement. The degree of granularity for the information elicitation depends on the abilities and practice of support seekers to enter input. Therefore, after roll-out, the CA should prompt support seekers for various information items to ensure coverage of required information. During operation, information categories can be reduced as support seekers become more experienced in using the CA. Moreover, information about support seekers' hard- and software that can be retrieved automatically should be improved.

13.7 Discussion

Motivated by the current weaknesses of CAs in autonomously delivering service, this study addresses the limited design knowledge to configure fallbacks in the form of handovers from CAs to service employees. More specifically, the current knowledge gap on CA-guided information elicitation during interaction with support seekers is tackled to prevent impending service failures by relaying information to service employees. Accordingly and in line with calls from research, we propose a hybrid service delivery scenario for online services (Coombs et al., 2020; Lacity and Willcocks, 2021). In this regard, a purposeful division and interconnection of service delivery activities between CA and service employee need to be ensured (Benbya et al., 2021). Therefore, we adopted a holistic socio-technical perspective to integrate requirements from the perspective of support seekers and service employees (Makarius et al., 2020). Thereby, we aimed to ensure that support seekers feel supported in providing information during the CA-guided service interaction so that service employees can easily complete the processing of the request after the handover.

Based on two consecutive DSR projects, we present evolved design knowledge in the form of four DPs to design the elicitation of information by CAs. To define the activities of the CA for a service script, we built on the established concept of facilitation that focuses on supporting individuals to achieve a task goal through interventions in a structured process. The user test evaluation has shown that the implementation of the DPs is feasible and leads to satisfactory interactions for support seekers. In particular, the proactively offered support and suggestions for prompted information items (DP2) as well as the friendly and respectful behavior (DP4) were rated positively. These results are substantiated by the finding that the CA has been evaluated as user-friendly and has the potential to increase the effectiveness of a request submission for support seekers. Overall, the evaluation with potential support seekers indicates that information elicitation is useful and DPs are applicable. In addition, the effectiveness of the CA was assessed by service employees, who analyzed the information elicited by the CA. To assess the characteristics of this information, a comparison was performed with information content from current tickets with the same thematic focus. The corresponding results underline the importance of DP1 and DP3, as the facilitating behavior of the CA provides a promising step-by-step approach to collect thematically appropriate information while ensuring mandatory items, leading to higher completeness as well as comprehensibility of CA-elicited information. Furthermore, DP2 yields an increased level of specificity and comprehensibility, as support seekers are better informed about prompted information by the CA via proposed explanations, suggestions, or examples. Equipped with this information after handover, the efficiency of request processing from service employees' point of view could increase and thereby reduce the waiting time for support seekers.

By using and evolving design knowledge from separate but related problem spaces, we provide prescriptive knowledge of the type "exaptation" according to the contribution framework of Gregor and Hevner (2013). With this design knowledge, we offer insights for research and practice on how to strengthen the robustness of CA-based service delivery in IT support in particular and for intangible online services in general. Accordingly, this study contributes to research on CAs, online service delivery, and future work scenarios. The results show that the focus in designing CAs should not only – as in previous research –meet the demands of support seekers but should also meet the requirements of service employees. Thereby, the successful continuation of request processing by service employees after handover can be ensured. Moreover, by linking the activities of the CA and the service employee, possible service failures could be reduced and hybridization of service provision can be achieved. These findings can be used to intensify the investigation of service recoveries via fallbacks to service employees by distinguishing between two handover types, which ensure the direct or delayed continuation of request processing. In our study, we applied the facilitation concept to the context of online service delivery. A novel approach to designing self-service interactions between support seekers and AI-based agents is provided by combining it with service scripts. Overall, the results show that this approach and the implementation of the DPs have the potential to produce improved working conditions for service employees by reducing the number of repetitive requests and providing support with relevant information after the handover from CAs. With the presented results, we contribute to facilitation literature, as we show that the concept can be applied to the online service context. For practice, we provide implementable design knowledge to guide the construction of interaction templates for CAs in the context of online service. In particular, organizations can benefit from the insight that hybridizing service processes via the integration of the activities of CAs and service employees might result in improved service quality.

Despite these valuable contributions, there are a few limitations to consider, which provide avenues for future research. First, the results show that the elicitation of information is satisfactory from the support seekers' point of view and service employees perceive it as supportive to continue request processing. However, to gain insights into the effectiveness of this hybrid work process in the future, the entire workflow should be evaluated in a naturalistic environment. In this context, it should be assessed whether handing over information that was elicited by the CA can reduce the overall number of service failures. In addition, it should be evaluated whether this hybrid online service delivery leads to expected relief for service employees and improved support seeker satisfaction. Second, the implementation of DPs in the CA prototype is limited to the elicitation of information to prepare handover. In future research, it should also be investigated whether the facilitative activities that guide support seekers in providing information can also increase the resolution rate of CAs and thereby avoid handover to service employees. In addition, the influence of support seekers' experience in providing information should be investigated to achieve a balanced granularity in the process of the CAs' information elicitation. In this regard, automated recognition of support seekers' input by the CA could be explored to provide personalized guidance that matches users' experience level. Third, for the study at hand, we considered the online service work context IT support, which has similarities to customer service in the organization of work (Davenport and Ronanki, 2018). To verify the applicability of the DPs to different service domains (e.g., finance, insurance), the design knowledge should be applied, implemented, and evaluated.

13.8 Conclusion

With this study, we address the current disconnectedness of the activities of CA and service employees during online service encounters with support seekers to enable hybrid service delivery. By evolving design knowledge across two DSR projects, we present DPs to design CAs that are capable of eliciting relevant information while interacting with support seekers. As a result, fallbacks with handovers to service employees can be realized to avert imminent service failures by CAs. The results of the study show that the design of a service script that bases on the concept of facilitation enables CAs to prepare a handover. The guidance with elements of flexibility in terms of on-demand support and feedback helps support seekers in providing relevant information in the elicitation process. By adopting a holistic socio-technical approach, the generated design knowledge meets the demands of support seekers concerning a satisfying interaction with a CA. Moreover, the elicited information supports service employees in continuing the processing of requests after the handover.

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14 Hybrid Service Recovery: Design for Seamless Inquiry Handovers between Conversational Agents and Human Service Agents

Poser, M., Singh, S., & Bittner, E. A. C. (2021). Hybrid Service Recovery: Design for Seamless Inquiry Handovers between Conversational Agents and Human Service Agents. In *54th Hawaii International Conference on System Sciences (HICSS),* Virtual conference.

Abstract

The effort of companies to deploy conversational agents (CAs) for customer self-service has been renewed due to their recent technological improvements. Despite their efficiency in processing recurring simple customer inquiries, limited capabilities of CAs to handle complex inquiries still lead to service failure and unsatisfied customers. Therefore, we propose a hybrid service recovery strategy with real-time handovers of inquiries from CAs to human service agents (HSAs), if CAs' capabilities are exceeded. Following a Design Science Research (DSR) approach, we present design principles (DPs) for the inquiry handover scenario, based on meta-requirements (MRs) derived from literature and expert interviews. By evaluating the DPs via prototype instantiation and process modulation, the suitability and interdependence of CAs' information collection activities and information presentation for handover could be verified.

Keywords: digital and cybernized services, conversational agent, design science research, handover, hybrid customer service

14.1 Introduction

As customer satisfaction depends on service delivery features such as availability and accessibility, organizations continuously generate service innovations to meet customers' high expectations in terms of service quality [1, 2]. With advancing technology, customer self-service has created opportunities to make service processes more efficient, save costs with reduced manual work and offer support at customers' convenience [1, 3]. Recent improvements in artificial intelligence, especially in machine learning (ML), have revived companies' efforts to adopt conversational agents (CAs), e.g. chatbots, to elevate the intuition, richness and simplicity of self-service interactions [4]. CAs' capability to mimic human-to-human communication by autonomously interacting with humans via natural language [5, 6] constitutes an effective means to quickly provide engaging customer service irrespective of manual service operating hours [7].

Despite their potential to improve availability and accessibility, CAs are still bounded in handling customer inquiries [8, 9]. That is, CAs' capabilities are mostly restricted to retrieving fact-based, predefined response types (e.g. FAQs) and processing recurring data-intensive requests (e.g. change pickup location for package) [10–12]. Requests that are more complex (e.g. how or why questions) or linguistically ambiguous often exceed CAs' problem-solving or language understanding capacity, could trap customers in conversation loops and leave them unsatisfied with an unsolved problem [13]. This experience may frustrate customers' expectations toward chat-based self-service and lead to drop outs in the service process [11, 14].

Thus, scholars call for service recovery strategies to compensate technological boundaries during service delivery and avoid customer dissatisfaction [15–17]. In this matter, previous research has focused on CA-initiated repair strategies to avoid conversational breakdown, ensure continuation of the dialog process and successful outcome [18, 19]. Nevertheless, repair attempts can fail repeatedly, customers' requests can be too complex for CAs to offer help or require handling by human service agents (HSAs) due to company policies (e.g. reimbursements) [11, 20]. Consequently, established fallback mechanisms that involve escalation of requests to HSAs are relevant to avoid complete service failures. However, to facilitate positive customer experience and meet customers' desire for short resolution time, approaches are required to assure real-time request processing by a HSA [19]. Therefore, instant chat-based handovers from automatic to manual processing are crucial to recover from CA failure. To realize this hybrid service recovery strategy, the design has to consider the socio-technical interplay of technology, processes and humans (employees and customers) and goes beyond technical system specifications [21–23]. To prevent customer frustration and support HSAs, relevant information of the CA-customer-interaction should be provided for the handover so that service process steps and questions do not have to be repeated [13, 17]. Therefore, connected processes are required to promote seamless handovers from CAs to HSAs [24, 25]. Moreover, CAs have to be configured to systematically collect information to present interim results to HSAs in a comprehensible format [25]. Hence, the goal of designing real-time inquiry handover as a CA service recovery strategy is addressed with the following research question: *How to design the point of customer inquiry handover between CAs and HSAs?*

The paper is structured as follows: Section 2 addresses the state of literature regarding CAs and customer self-service. Subsequently, the applied Design Science Research (DSR) approach is outlined. In Section 4, design principles (DPs) are presented, based on meta-requirements (MRs) from literature and expert knowledge. Section 5 presents the results from expert interviews to evaluate a DP-based mixed-fidelity prototype and process model. Results, contributions and limitations of the paper are discussed in Section 6.

14.2 Related work

14.2.1 Conversational agents

CAs are software systems, which interact with humans via natural language (voice, text or both) [6, 26, 27]. Several terms (e.g. chatbot, dialog system, cognitive assistant) are used to refer to CAs with different communication modes, representations and application contexts (general-purpose vs. domain-specific) [26, 28]. Since the initial CA (ELIZA) [29], technological advancements in ML and natural language processing (NLP) have led to a significant expansion of CAs' capabilities [30]. In customer service, CAs are primarily used to scale the provision of efficient assistance (e.g. complaint management) and information (e.g. for products) 24/7 to customers in different contexts [10, 31]. As such, chatbots are increasingly used as a text-based customer-facing channel for service delivery [32, 33]. However, due to the complexity of natural language conversations and their basic model of human interlocutors, CAs still have shortcomings in responding to a wide range of topics and complex inquiries [13, 34]. Furthermore, customers' high expectations toward CAs' conversational capabilities lead to breakdowns [35]. These problems are related to deficiencies of the natural language understanding and dialog management components, which interpret input wrongly, hinder dialog process (intent and/or entity detection) and prevent information retrieval or action execution [19]. As a result, customer requests are misinterpreted, answered inappropriately (false positive) or issues remain unanswered (false negative) [36]. Thus, a large number of requests needs to be directly or eventually escalated to employees [11].

In research, different approaches exist to overcome CAs' technical boundaries. On the one hand, users are prompted to engage in conversational repair activities by replying to CAs' uncertainty expressions (with or without alternatives) or rephrasing their input [18, 20]. On the other hand, employees are involved to avoid breakdowns by selecting an appropriate answer from CAs' suggestions [12, 37]. Nevertheless, existing approaches do not yet provide effective strategies for escalating requests to HSAs, (1) for which repeated repair attempts have failed or (2) which require employee handling as an (interim) result of a conversation. For such cases, an adaption of fallback solutions is needed where requests are deferred to employees. To avoid negative effects in terms of customer dissatisfaction due to additional waiting times, these solutions should address the challenge of real-time support [19]. The seamless handover of requests from CAs to HSAs as a recovery strategy addresses the suggestion in the literature of transferring requests to employees, if CAs' capacities are exceeded [12, 17, 32, 38].

14.2.2 Customer (self-)service

Companies aim to provide satisfying high quality service to customers, while increasing the efficiency and cost-effectiveness of service delivery. To ensure this, the design of the nature of daily service encounters with customers is of particular relevance to companies as they affect customer loyalty and consequently firm profitability [39]. In the past, service encounters were restricted to direct dyadic interactions between customers and employees, which are characterized by personalized and flexible service delivery with immediate feedback and elements of emotionality [39, 40]. With evolving technology, service innovations have increased the range of service interfaces allowing companies to interact with customers through HSAs, technology or a combination of both (e.g. webpages, email, chat) [1, 41, 42]. This development has led to a successive transformation of customer-company interactions from personal and dialog-based to automated self-service [43]. Despite the advantages of accessibility and availability, self-service technologies are more standardized, less personalized and less interactive compared to personal service channels, which hamper value creation and customer experience [3, 40]. To increase the effectiveness of technology-infused self-service encounters in terms of customer experience, service providers increasingly deploy intelligent technology [8, 33]. With CAs' capabilities to conduct intuitive human-like conversations, to elicit feelings of social presence, empathy and personalization in customers, companies become able to emulate the beneficial characteristics of personal service encounters in self-service solutions [9, 28, 44]. In addition, CA technology has enabled companies to make service more efficient by reducing the number of routine requests that need to be handled by HSAs, while increasing the convenience of service delivery for customers [3, 33, 40].

To fully take advantage of CAs and ensure high quality service, scholars call to investigate conditions, implications of and recovery strategies for service failure [15–17]. This knowledge is especially important for the prevention of detrimental effects connected to possible failures by CAs (e.g. for complex inquiries), as customers' satisfaction for service encounters with self-service technology inter alia depends on effective service recovery [45]. In this regard, the involvement of HSAs can ensure customer retention and avoid the abonnement of the self-service channel [14]. Therefore, to realize an effective CA service recovery strategy, service processes are required that enable the integration of multiple service interfaces [41]. Moreover, as satisfaction with the outcome of service recovery depends on interaction- and process-related factors [46, 47], a well-designed process for the request handover is required to avoid repetitive service delivery steps. This design should promote effective and efficient processing by HSAs, who take over inquiries from a CA in real-time.

14.3 Methodology

This paper presents a DSR project, which is structured in accordance to Hevner's [48] three cycle view (see Figure 1). By starting the relevance cycle, a relevant real-world problem is identified that pertains to the improvement of repair strategies involving request escalation to HSAs to avoid CAs' service failures (Section 1 & 2, step 1). The derivation of MRs for the design of and process for the customer inquiry handover is achieved, on the one hand, by considering domain specific knowledge of six experts with semi-structured interviews (Section 4.2., step 2) [49]. The interviewees (I) (age: 26-35; male: 4; female: 2), have experience in handling product-, service-, or technology-related inquiries from external customers and/or developing chatbot systems for the customer service of different organizations. For the semi-structured interviews, a guideline with three thematic categories was developed: (1) work and service processes, (2) CAs in service and (3) hybrid service. The qualitative content analysis of the transcribed interviews, which lasted 42 minutes on average, was conducted with MAXQDA software according to Mayring [50]. The iterative and open coding approach was performed deductively and inductively by defining (sub-)categories and corresponding coding rules referring to literature (e.g. initial service encounter, service recovery) and transcript content (e.g. information gathering, timing of service recovery). On the other hand, in the rigor cycle, MRs are derived from scientific literature (Section 4.1., step 3). In the design cycle, action and materiality-oriented DPs according to Chandra et al. [51] addressing the MRs are utilized to instantiate a mixed-fidelity prototype and a BPMN-based service process for the handover (Section 5.1., step 4). The two instantiations are demonstrated to five experts (female: 2; male: 3;age: 25-32) with experience in processing product-, service-, or technology-related inquiries as an external customer-facing service channel of different organizations (Section 5.1., step 5). By presenting both instantiations to the experts, the validity of implemented DPs was assessed by focusing on (1) the depicted CA's approach and the information presentation to assist HSAs in taking over an inquiry as well as (2) the process step sequence. For the evaluation (Section 5.2., step 6), semi-structured interviews were conducted with the same group of experts [49]. The interviews lasted 28 minutes on average and covered questions on the utility and suitability of the presented instantiations and underlying DPs. The content analysis was performed with a deductive coding approach utilizing MAXQDA [50]. The rigor cycle (step 7) is closed by adding prescriptive knowledge of form and function to literature, which contribute to a "theory of design and action" (Section 6) [52].

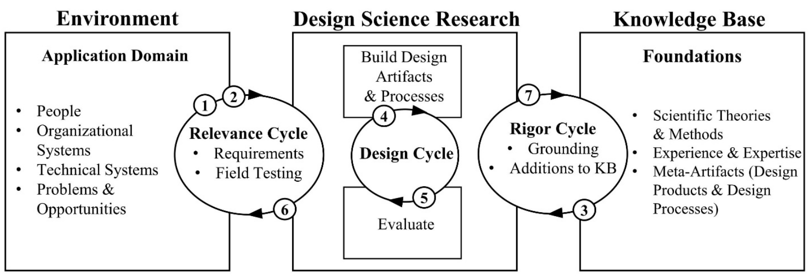

Figure 1. DSR three cycle view [48]

14.4 Design requirements and principles

Customers' evaluation of the outcome of a service recovery (e.g. rectification) depends on interactional and procedural factors [46, 47]. These factors encompass communication with and treatment of customers (interactional) as well as process execution for the recovery (procedural) [47]. The identification of relevant insights from theory and practice was structured with the (1) initial service encounter and (2) service recovery phase regarding interactional and procedural factors [46]. As a result, a set of MRs, constituting the basis for the DPs, was derived by drawing on literature (L-MR) and practical knowledge (P-MR) from experts in the field of customer service operations.

14.4.1 Meta-requirements from literature

Initial service encounter: For the service encounter, customer satisfaction with technology-infused self-service channels depends on the responses to their needs and requests as well as the avoidance of systems' unprompted actions [45, 53]. Thus, CAs should understand intentions or problems of customers to provide suitable assistance or solutions (L-MR1.1) [18, 32]. The identification and handling of inquiries should be addressed by maintaining a conversation with the customer that has the character of a natural dialogue (L-MR1.2) [31, 54]. During this conversation, the CA needs to be capable of interpreting customers' intentions by considering both the individual messages and the overall interaction context (L-MR1.3) [55]. In addition, the CA should prompt customers with questions to provide more details, if the inquiry is missing relevant information (L-MR1.4) [20, 56]. To converse via natural language, CAs need robust NLP capacity to automatically analyze input and generate adequate answers [5, 11, 19] (L-MR1.5). ***L-MR1:*** *CA needs to interpret messages and interaction context to understand the inquiry, while conversing with a customer.*

Service recovery: For service recovery, customer satisfaction depends on the response to a service failure [45, 53]. Therefore, the CA should actively initiate handovers, if an inquiry exceeds the linguistic or problem-solving capabilities during customer interaction (L-MR2.1) [20, 38]. The CA needs to be aware of the service delivery process and monitor the status in order to anticipate service failure incidents (L-MR2.2) [13]. ***L-MR2:*** *CA needs to respond to a failure by actively initiating the handover*. CAs deliver service in real-time, which means that the reason for a service failure cannot be analyzed prior to the incident [57]. Accordingly, the CA should identify relevant information during customer interaction to make corresponding data entries accessible from business applications (e.g. on product or customer) [28, 58] after the handover (L-MR3.2). ***L-MR3:*** *CA needs to identify supplementary data available from business applications for the recovery.*

14.4.2 Meta-requirements from expert interviews

Initial service encounter: During the initial service encounter, an important perquisite for CAs constitutes the preparation of the handover by systematically gathering information (I1, I3). In this context, the CA should attempt to comprehend and categorize the concern or question of the customer during the conversation to determine further steps (I1, I3, I4, I6) (P-MR1.1). Furthermore, CAs' capability to understand the context in a longer conversation is fundamental (I3, I5, I6) (P-MR1.2), since customers require varying time amounts to formulate the core of their request (I2). ***P-MR1:*** *CA needs to comprehend and categorize an inquiry by capturing the conversational context*. The documentation of inappropriate or incorrect information that makes further processing by HSAs cumbersome must be avoided (I1, I3). Thus, the CA should differentiate between valuable and irrelevant content (I4) (P-MR2.1). Accordingly, the CA should actively pose a set of relevant questions (I5). If there are ambiguities, follow-up questions need to be asked. The questions should be precise and their intentions have to be transparent to the customer to receive applicable information (I1, I6) (P-MR2.2). ***P-MR2:*** *CA needs to pose initial and follow-up questions for ambiguous input and convey their intention to determine relevant information*. The CA should encourage customers to describe the problem to determine its content (I3) (P-MR3.1). Doing this, CAs' behavior should be characterized by polite and goal-directed behavior (no double questions) (I5), to maintain customers' satisfaction and willingness to cooperate (I1, I2) (P-MR2.3). ***P-MR3:*** *CA needs to act politely and goal determined to maintain customer's satisfaction*.

Service recovery: In general, a CA should enable customers to forward their requests to a HSA at any time during the interaction (I1, I2, I3, I4, I6) (P-MR4.1). In addition, a complete abortion caused by CAs' technical boundaries should be prevented to offer handovers as a service recovery (I6) (P-MR4.2). ***P-MR4:*** *CA should offer handover options throughout interaction and prevent customer abortion before handover*. The initiation of the recovery by the CA should base on different parameters. The inquiry handover should be introduced by the CA, if a certain amount of time (I2, I4) or a maximum number of failed attempts in the form of questions or propositions (e.g. three (I1, I5) has been reached (I3, I4, I5, I6) (P-MR5.1). Therefore, the CA needs to register malfunctioning conversations caused by misguiding questions and unfitting solution proposals (I2, I4, I6) (P-MR5.2). ***P-MR5:*** *CA needs to register misleading questions and solution proposals to initiate handovers adhering to defined limits of time and/or unsuitable propositions*. A HSA should be forewarned by the system to prepare the continuation of the inquiry processing to realize an efficient real-time handover without delays (I3, I6). Once a recovery has to be initiated by the CA, essential and available information extracted from the interaction between CA and customer should be compiled for the HSA (I1, I3) (P-MR6.1). In addition, the CA should verify and supplement information from the conversation by accessing databases (I4, I6) (P-MR6.2). The arrangement of visualized information needs to be standardized and concise so that HSAs can see the core elements of the request at a glance – in resemblance to a ticket system (I1, I3) (P-MR6.3). ***P-MR6:*** *The presentation of information from the interaction and databases should be standardized and concise*. For a workable information presentation, the determined cause of the request needs to be provided (e.g. problem/complaint, product order) (I1, I3, I5) (P-MR7.1). Furthermore, the identification of the inquirer and/or object of inquiry should be presented (I1, I3, I6) (P-MR7.2). In addition, details referring to solution attempts by the CA (I1, I2), documentation and short description of the conversation (I1) as well as a recommendation for a solution (I2, I4) should be generated. Moreover, applicable data from business applications, such as known errors and past decisions (I3, I4, I5), should be included in the inquiry summary (P-MR7.3). ***P-MR7:*** *The information presentation should capture cause of request, inquirer or object of inquiry, documentation of the interaction, supplementing database entries and recommendation*.

14.4.3 Design principles for inquiry handovers

Based on the MRs, five DPs are defined. The DPs are of the types form and function with substantial properties, capturing prescriptive knowledge to generate solutions for a hybrid service recovery strategy with real-time handovers from CAs to HSAs [59]. Following a supportive research approach [60], ten MRs were elicited. Three MRs emerged through knowledge from literature, seven MRs were obtained through interviews. The MRs and corresponding DPs are organized according to two categories, which emerged through the deductive-inductive coding process: (1) information collection and (2) information transfer (see Figure 2).

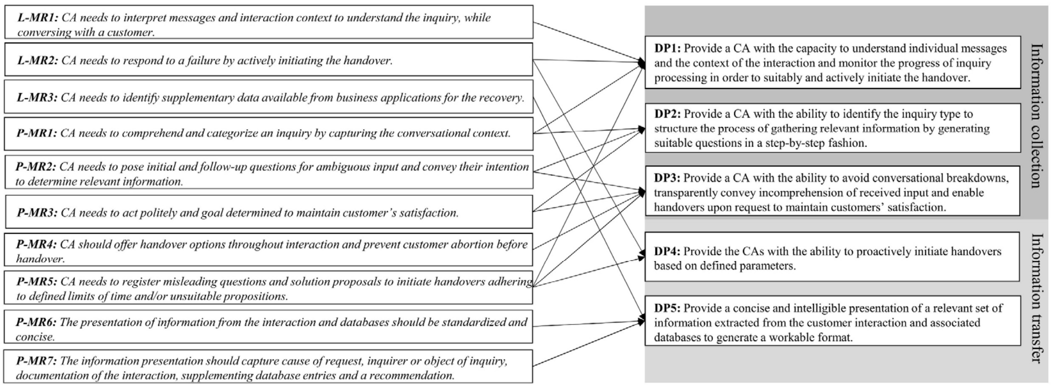

Figure 2. Meta-requirements (MR) and derived design principles (DP)

Information collection: The collection of information is a prerequisite for efficient inquiry handovers. Thus, the CA should be capable of tracking the inquiry processing progress and understanding individual messages and the context of the interaction to initiate the transfer in a suitable moment (***DP1***). HSAs require an information basis to continue the processing of a transferred inquiry in real-time. Thus, to gather relevant content and avoid the transfer of incorrect information, the interaction between customer and CA should be sustained by the ability of the CA to categorize the inquiry type (e.g. complaint) to subsequently generate suitable questions step-by-step (***DP2***). To avoid service failure during the initial service encounter, the CA should be able to avoid conversational breakdowns before inquiry handover and maintain customers' satisfaction and willingness to cooperate by transparently revealing incomprehension of input as well as enabling handovers upon customer request throughout the process (***DP3***).

Information transfer: The prevention of service failures requires the capability of a CA to proactively initiate inquiry handovers to a HSA, if technological boundaries have been reached. This handover initiation should base on adequate predefined parameters (***DP4***). For the service recovery by HSAs in real-time, the presentation of relevant information is a fundamental prerequisite. This information should be extracted, both, from the interaction with the customer and suitable databases. The presentation needs to be clearly structured and in a workable format (***DP5***).

14.5 Evaluation

14.5.1 Demonstration

The demonstration of the instantiated DPs was achieved with a mixed-fidelity prototype and a BPMN-based process depiction addressing interactional and procedural aspects of the inquiry handover. The web-based proof-of-concept realized with HTML, CSS and JavaScript shows a script-based and chronological sequence of an interaction between customer and CA. The exemplary dialog was conceptualized with experts' descriptions of complaint inquiries, which exceed CAs' problem-solving capabilities. The prototype displayed messages in a chat window (Figure 3 left side for an excerpt) beginning with the first contact and ending with the initiation of a handover to a HSA (DP3 & 4). In addition to the conversational sequence, compiled information for the handover, gathered from the exemplary interaction and conceivable databases, is displayed (DP5) (Figure 3 right side). The process model with BPMN shows the individual steps of the initial service encounter and service recovery (see Figure 4). In line with the DPs, the customer has the option to abort the CA interaction and request a handover throughout the process (DP3). The information acquired from the customer (DP1 & 2) is aggregated and supplemented with database entries to collect information for the handover (DP5). The handover is actively initiated, if more than three unfitting solutions have been proposed by the CA (DP4).

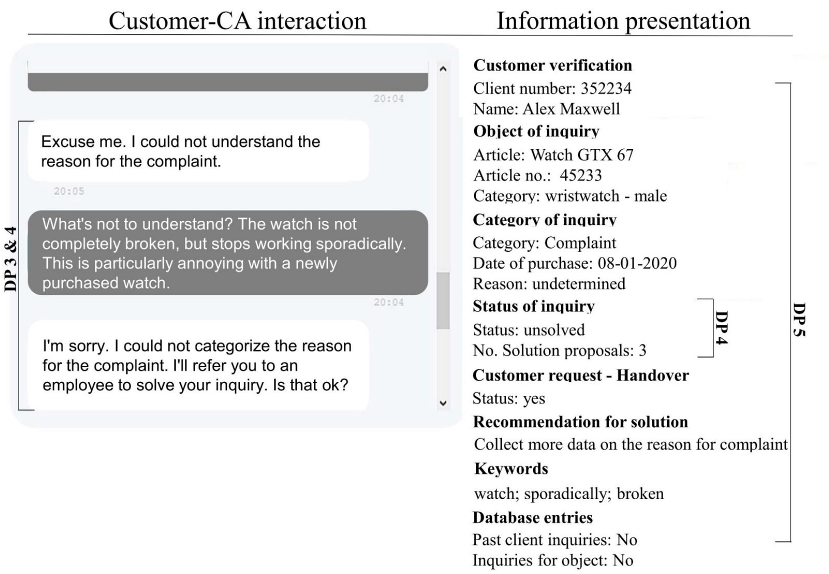

Figure 3. Web-based proof-of-concept

In order to verify the validity of the DPs, experts in customer service request handling watched the exemplary dialog, assessed the extracted information and depiction of the process. In general, the experts evaluated the instantiated DPs as suitable and applicable. Concerning DP1, the prototype showed an exemplary level of speech comprehension and dialog flow, which was rated as accurate and adequate. For the systematic collection of information (DP2), the experts considered the procedure of specifying and identifying a category of an incoming inquiry as efficient and appropriate. With regard to DP3, the experts agreed that the CA has to maintain the interaction with customers in order to extract substantive information from the conversation before the handover. The ability and procedure of the CA to actively initiate handovers were addressed regarding DP4. Experts stated that the faster a handover is triggered in the event of problems, the better. In accordance with the prototype, it was confirmed that the number of proposed unsuitable solutions by the CA constitutes a functional threshold for the initiation of a handover. Lastly, the experts evaluated the compilation and visualization of information. The prototype displayed following items: identification of the inquirer and/or object of inquiry, inquiry category and content, number of processing attempts, recommendation for continuation, keywords and conversation, historical database entries about the inquirer and/or object of inquiry. These items were rated to be both useful and helpful to instantly proceed after the handover (DP5).

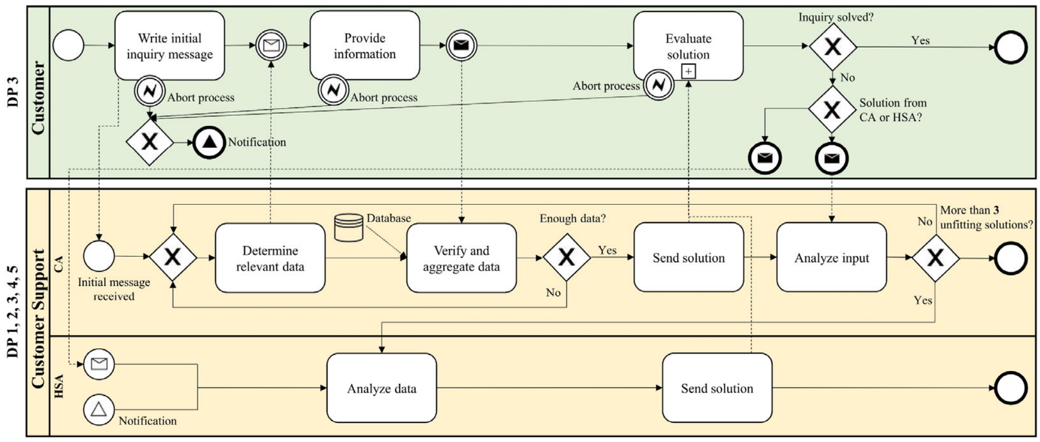

Figure 4. BPMN-based handover process with DP annotations

14.5.2 Expert assessment

The experts considered the process sequence to be useful and practicable in order to facilitate HSAs in processing an inquiry after a real-time handover from a CA. In accordance to the prototypical CA interaction that manifest the modelled process steps, the experts validated the interdependence of CAs' information collection activities and information presentation for the process continuation by HSAs. Regarding DP1, the experts emphasized the importance of a solid understanding of language so that a request can be partially prepared for HSAs before handover. The CA's approach to systematically collect information was discussed to address DP2. Experts perceived the ability of the CA to identify the category of an inquiry as highly relevant. This capability enables the CA to subsequently pose relevant inquiry-specific questions. One expert expressed: "It makes sense to approach the problem step by step. If the CA knows what the inquiry is about, it can ask specific questions. Often only then you get the really important information." As a limitation, it was mentioned that inquiries can be ambiguous comprising several intentions, which complicates definite category allocation. As a result, a CA could develop the dialogue in the wrong direction from the start and incorrectly classify information. Therefore, CAs' capability for adaptive interaction and reassurance regarding customers' intentions is important in order to gather information through suitable questions. With regard to DP3, transparency of behavior in terms of CA's feedback to customers concerning input processing problems is considered crucial to support customers' technology acceptance. One of the experts stated: the CA should "describe, [...] in which situation it is currently, whether it can proceed solving the problem or still has problems." The CA's request of customers to supplement or reformulate their input is helpful for maintaining the conversation. However, despite the relevance of transparent behavior, the CA should not repeatedly explain its shortcomings in detail to avoid customer frustration. The experts consider the option for customers to request a HSA, regardless of the service process stage, as mandatory to avoid customers' feeling of being dependent on the CA. In contrast to the presented process steps and prototype, one expert emphasized that customers who request a handover should be obliged to provide a minimum set of information (e.g. process number) to facilitate HSAs in continuing the inquiry processing and save valuable time. In addition, experts emphasized that structural changes need to be implemented to avoid overstressed HSAs and excessive rates of requested handovers from customers. Accordingly, one expert expressed that "if capacities are limited, it makes sense not to offer the possibility of a handover from the beginning, as otherwise the employees could be strained." The approach of CAs' initiation of handovers was discussed with respect to DP4. For the evaluated instantiation, the threshold was set at three failed attempts before the CA triggered the handover. This number was rated to be too high by two experts considering customers' patience. The specification of the threshold was determined to be use-case- and customer-specific and should not merely base on "human-oriented experience values" regarding inquiry processing standards. The exceedance of time limits as a threshold for handover initiation was considered as inappropriate, because the duration for an initial service encounter depends on customers' ability to engage with technology and communicate their intention. Regarding the format and types of information for the handover (DP5), the experts considered the presentation as valuable. One expert said that the "information was presented in a well-structured way". For the majority of experts, the most important information constitutes the identification of the inquirer and/or object and the content of the request. Particularly, two experts positively evaluated the summary of the conversation with keywords. The information presentation was assessed to facilitate the continuation of inquiry processing, as it allows more targeted questions and time saving searching for suitable information. The preparation of database entries is useful and offers the possibility to personalize the interaction with the customer. However, the overall applicability of database entries depends on the usage context and suitability of displaying historical data.

14.6 Discussion and conclusion

The objective of the paper was to develop a hybrid service recovery strategy for CAs in customer service. In line with companies' endeavor to increase efficiency of customer service with self-service technology by simultaneously reducing customers' dissatisfaction with CAs [1, 9], we present initial design knowledge for real-time handovers to HSAs, which are initiated before CAs' service failure. The prescriptive design knowledge provides a solution to effectively and instantly escalate requests, if (1) CA-initiated repair attempts in collaboration with customers have failed or (2) they require HSA handling (e.g. due to company policies). The derived DPs embrace resource-friendly inquiry processing by considering, both, requirements for CA-customer interaction and the compilation of suitable information concerning the handover.

The results of the evaluation confirm the suitability of the applied DPs in the instantiated prototype and process model. Overall, experts stated a positive perception toward the hybrid approach to execute service recoveries. They affirmed that efficient handovers require a concise compilation of critical and manageable information from the customer-CA interaction and associated databases for a seamless continuation of inquiry processing. The evaluation has further shown that the proposed process steps are applicable. However, the implementation requires a substantial restructuring of service processes to ensure the availability of HSAs for real-time handovers, while taking into account their time and mental capacities. Experts further emphasized the importance of a context-specific determination of parameters and information items for the handover. Thus, the threshold for proactive handover initiations by CAs should comprise multiple data points from the customer-CA interaction covering aspects of time and CAs' solution or repair attempts.

With the presented MRs, DPs and instantiations, theoretical and practical contributions are provided. We contribute prescriptive knowledge about form and function with an initial set of design principles for research to guide the interlocking of CAs and HSAs to improve service recoveries, which incorporate request escalation [13, 19]. We also contribute to service literature by addressing the identified need in literature for improved service recovery strategies for CAs involving HSAs [12, 13, 17, 32, 38]. Established fallbacks involving request escalation are extended by providing a holistic service recovery strategy for CAs, addressing the challenge to provide real-time support and incorporating valuable insights from theory and experts in the field of customer service. With regard to practice, the DPs constitute a deployable design blueprint for organizations that aim to implement or improve service recovery strategies for CAs. This can serve to invoke, both, short resolution time for customers and support for HSAs to seamlessly continue processing inquiries after the handover. Apart from the promising results, there are some limitations to consider. The gathering of practical MRs and evaluation are limited to two independent samples of experts with a restricted demographic diversity. The insights are confined to their experience in handling inquiries representing customer-company encounters. However, following an iterative approach, further instantiations in future design cycles, will potentially generate supplementary practical knowledge. To enrich the nascent state of scientific knowledge, in future research the presented solution should be investigated in the application context and compared with existing market solutions that facilitate handovers from CAs to HSAs. Furthermore, the DPs should be implemented in a functional prototype to gain further insights about the applicability of the process steps and improvements of the artefact to the operational environment. Perceptions of employees regarding the usefulness of presented information need to be investigated in real-world usage scenarios. In this regard, mechanisms of an alert system should be developed and investigated addressing aspects of time and function to warn employees about upcoming handovers. The perspective of customers should also be addressed to assess the effect of real-time handovers on their satisfaction. Furthermore, future research should address the restructuring of service processes to integrate multiple service interfaces (CA and HSA) for effective service delivery and recovery. Lastly, the generalizability of the design should be validated for related service contexts such as intra-organizational service encounters (e.g. IT-helpdesk).

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15 Don’t Throw It Over the Fence! Toward Effective Handover from Conversational Agents to Service Employees

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Abstract

Contemporary conversational agents (CAs) are capable of reliably answering repetitive low-complexity requests in online customer service, but regularly breakdown when dealing with high content or semantic complexity. The resulting service failures have a detrimental impact on customers’ satisfaction and their willingness to use CAs in the future. By aiming to avert CA breakdown in service encounters with a hybrid service recovery strategy via handover UI, we address a knowledge gap in service literature. As automated recovery strategies via conversation repair do not invariably prevent CA breakdown, real-time handover of customer interaction from CA to service employee (SE) is increasingly applied and investigated. This hybrid service recovery strategy places high demands on SEs, as they must keep waiting times short and avoid repetition of questions to customers after handover. Considering SEs limited cognitive capacities for information processing, we present a handover user interface (UI) with relevant information to support SEs after handover. Following a Design Science Research approach, we define design principles for the handover UI, based on meta-requirements derived from kernel theories and expert interviews. By evaluating the design principles via prototype instantiation, we show that the information types and their presentation in the handover UI keep cognitive efforts for SEs at a manageable level and help them initiate customer interaction quickly.

Keywords: Handover, Hybrid Service Recovery, Conversational Agent, Customer Service

15.1 Introduction

Digitalization in all areas of life creates expectations concerning the ubiquitous accessibility and availability of information in general and of digital services in particular. To meet these changing demands, service companies in various industries (e.g., e-commerce, finance, IT) have increasingly automated online customer service (OCS) encounters with self-service solutions [1, 2]. With the objective of improving efficiency, personalization, and quality of these automated customer-facing interactions, companies are steadily deploying conversational agents (CAs), such as chatbots [3]. Powered by recent developments in machine learning (ML), CAs are capable of autonomously interacting with users via natural language in a human-like fashion [4–6]. This allows intuitive and engaging service interactions with customers in a large number of simultaneous encounters [7]. At present, CAs are capable of reliably answering repetitive, predictable, low-complexity requests from customers [8]. However, requests with high content or semantic complexity exceed the bounded capabilities of CAs and lead to conversation breakdowns or loops [9, 10]. As such service failures result in unanswered customer matters [11], value might get deconstructed and customer satisfaction could be jeopardized [12, 13].

To avoid CA failure, so far, automated repair strategies have been investigated to minimize conversation breakdowns [14, 15]. However, this form of service recovery does not work when repeated repair attempts have failed. Therefore, real-time handover of the preceding customer interaction from CA to service employee (SE) is increasingly applied and studied as a promising fallback mechanism [14, 16–18]. This hybrid service recovery strategy places high demands on SEs, as they must keep waiting times short and avoid repetition of questions to customers after handover. Hence, to ensure the efficiency and effectiveness of service delivery after CA failure, a handover solution is required that supports SEs to seamlessly and effortlessly continue request processing [19, 20]. However, handover as a service recovery strategy is so far under researched, needs of SEs in hybrid work settings have been given little consideration, and the required interplay of CA and SE in socio-technical systems of companies' customer service is not yet well developed [2, 14, 21]. To address these knowledge gaps, we develop a requirements-based user interface (UI) to support SEs after handover, so service delivery can continue efficiently after CA failure. Accordingly, we address the following research questions (RQs): *RQ1: How should a handover UI be designed from the perspective of SEs for instant request processing after handover? RQ2: What effect does the use of the handover UI have on SEs' behavior toward and perception of the UI?*

To answer these research questions, we present the second design cycle of a larger Design Science Research (DSR) project. With the aim of allowing seamless continuation of chat-based service encounters after CA failure by SEs, we derive prescriptive design knowledge via theoretical insights and expert interviews. The instantiation of a prototype serves to evaluate the efficiency of a UI that allows to adopt a hybrid service recovery strategy for CAs. The remaining paper structure unfolds as follows. First, we present the conceptual background by elaborating on trends in OCS and hybrid service delivery. Next, we describe our research approach, outline the derivation of the design knowledge and demonstrate its instantiation in a web-based prototype with UI. Subsequently, we present the results of a mixed-method evaluation. We close with a discussion of obtained insights and provide an outlook for future research.

15.2 Conceptual Background

15.2.1 Online Customer Service and Service Failure

Spurred by digitization, organizations' delivery of intangible services directed toward objects or people has been fundamentally transformed [22, 23]. Based on technology-driven service innovations, self-service solutions have emerged that allow efficient service production via online channels enabling high service quality and customer satisfaction [1, 24]. The investigation of various self-service technologies has proven their capability to rapidly, conveniently, and cost-effectively deliver service to customers [25]. To capitalize on technical progress and elevate customer experience, the role of technology that is based on artificial intelligence (AI) has increasingly been explored and investigated in recent years [21, 26, 27]. As such, AI-based CAs have been studied and deployed in research and practice as they meet current customer demands for personalized, bidirectional, and chat-based service encounters [28, 29]. CAs are defined as intelligent software systems that communicate with users via spoken or textual natural language [4, 5]. To create and improve personalized service experiences with a human-like touch, previous research has investigated interaction-related as well as technical aspects of CAs (e.g., response time, appearance) [30–33]. However, despite their potential and technical advances, CAs are still prone to fail [13]. To identify the underlying reasons, previous research has initiated the investigation of different types of conversation breakdowns and derived distinct automated repair strategies [14, 16, 34]. If these strategies do not hinder CA breakdown in service encounters, service failures occur which causes customer dissatisfaction and compromises the benefits of CAs.

In literature, service failures are defined as the incapacity of service providers to deliver desired outcomes or processes [11]. As these failures are ubiquitous and insights in relation to their implication for AI-based service delivery are scarce [35], research effort has been devoted to generate insights on the effects of AI-based failures (e.g., effect on perceived humanness, service satisfaction) [36, 37]. In addition, initial research has explored the effectiveness of service recovery strategies. So far, strategies with informative explanations or immediate assistance have been examined to avert the negative impact of service failures on customers' satisfaction [38, 39]. As strategies with immediate assistance are more promising due to their likelihood for recovery success and short waiting times for customers, handovers to SEs are increasingly investigated [14, 40]. Until now, however, there is a lack of knowledge on how to implement this particular service recovery strategy.

15.2.2 Hybrid Service Delivery

The integration and adoption of AI in organizations requires fundamental modifications of service systems, processes, and interactions between customer, AI, and SE [41–44]. As a result, hybrid service delivery settings are emerging that transform the service encounter

[2]. In this regard, [45] distinguishes between three AI-based encounters: AI takes over the interaction and co-creation with the customer in **(1) AI-performed** encounters. **(2) AI-supported** refers to the assistance of the SE by an AI application during the interaction invisible to customers, whereas in **(3) AI-augmented** AI is visibly involved to assist the encounter with the customer. These innovative forms of customer interactions allow the exploitation of respective strengths of AI and SEs in terms of specific requirements during service delivery. **AI-supported** and **AI-augmented** encounters are suitable to answer complex customer requests. As AI is, inter alia, capable to quickly sift through large amounts of information to identify and suggest suitable solutions, human limited information processing capacity can be compensated [46]. Complementarily, humans can contextualize presented suggestions by the AI. In addition, emotional needs of customers can be addressed by SEs [47].

In **AI-performed** encounters large amounts of simple customer requests can be solved. However, as current AI solutions, such as CAs, only reliably answer repetitive and information-intensive requests that require low to high analytical abilities, the risk of service failures for complex customer issues remains [26]. To mitigate the impact of these failures, an optimization of the integration of CA and SE work processes is needed to develop hybrid service recovery solutions [39]. More specifically, in OCS, solutions are required that, on the one hand, meet customers' demands for fast service delivery, as they overestimate the time spent in queue and long waiting time has a negative impact on their satisfaction [18]. On the other hand, SEs should be enabled to avert service failure via handover [40]. To meet these requirements, design approaches are required to create a UI that enables the integration of CA and SE work processes. Related research on the design of UI has shown that features of the interface can help to accommodate humans' limited resources for attention and information processing [48]. As users direct attention to stimulus features, they can be assisted to process task-relevant information by different design elements (e.g., font size, color) [49, 50]. Thus, to enable a timely continuation of the customer encounter, information presentation in a handover UI should be adapted to human factors [51]. To date, however, there is no design knowledge on the subject of handover UI [14, 40].

15.3 Research Approach

To answer the proposed RQs, we follow the DSR approach, which represents an established research paradigm to construct socio-technical artifacts for prevalent problems [52]. We structure our research project with the methodology of [53], covering two design cycles to ensure evolving maturity of developed design knowledge and created design entities (see Fig. 1).

In the *first cycle*, we established a general understanding of the demand for handovers from CA to SE to avoid service failures based on current findings in literature and interviews with domain experts. Building on these insights, we commenced by generating initial design knowledge in the form of tentative design principles (DPs) for the handover process, the collection and transfer of information by the CA before handover. By demonstrating and evaluating a non-interactive mixed-fidelity mock-up prototype based on these DPs, we provided a proof-of-concept [40].

DSR activities	Cycle one	Cycle two
(1) Problem Identification	Insufficient recovery strategies for CA failure in service encounters	Lack of support for SEs to enable efficient handover
(2) Objectives of a Solution	Real-time handover from CA to SEs	Handover UI for SEs
(3) Design & Development	Interaction and process design for CA handover	UI prototype based on design principles
(4) Demonstration	Implementation of CA handover with non-interactive mixed-fidelity (mock-up) prototype	Implementation of web-based UI prototype
(5) Evaluation	Qualitative expert evaluation to provide a proof-of-concept	User test for mixed-method evaluation of handover UI
(6) Communication	[40]	This publication

Figure 1. DSR approach and design cycles

In the *second cycle*, which is the focus of this paper, the DPs from the first cycle are extended. In this context, as part of **(1) Problem Identification**, the problem relevance was reconsidered by identifying a lack of support for SEs to enable efficient handovers. Hence, within **(2) Objectives of a Solution**, knowledge from applicable kernel theories and insights from application domain experts were used to determine meta-requirements (MRs) for a handover UI that assists SEs in continuing the service encounter instantly after handover. In semi-structured interviews, six experts (E1-6) participated with experience in chat-based service encounters to handle customer requests. The interviews followed a pre-defined structure with questions about their current working reality, a demonstration of the proof-of-concept from cycle one followed by questions about its applicability and requirements for a suitable handover UI. Based on verbatim transcripts, a qualitative analysis of the interviews following the approach of [54] was conducted. Using MAXQDA 2020, two researchers inductively formed code categories by defining and revising rules and categories iteratively working through the transcripts. To ensure objectivity, code sets were continuously harmonized resulting in four main categories (e.g., information requirements handover) and nine sub-categories (e.g., volume of information). Using these insights, MRs were identified and DPs formulated according to [55]. For **(3) Design and Development** and **(4) Demonstration**, the generated DPs were instantiated. Based on defined design features (DFs) that refer to underlying DPs, a web-based prototype was implemented. For the **(5) Evaluation**, we assessed the prototype in user tests. Ten participants (PA) (three female and seven male) from different organizations with experience in handling service- or technology-related requests in OCS from different business fields (e.g., e-commerce, market research) were instructed to seamlessly continue service encounters after handover. In this evaluation setting, the semi-automated technical prototype supported PAs with information whose display was manually triggered by an involved researcher. In addition, detailed information was automatically displayed after button click by PAs. To simulate a natural working situation, the PAs were instructed to handle a customer request referring to a technical problem (laptop battery does not charge) and provided with applicable knowledge prior to the user test to resolve the problem. In subsequent interviews, PAs were asked about the fulfillment of the generated DPs and the impact of the handover UI on their work. To structure the interviews, questions were asked about (1) general impression of handover UI, (2) task processing with handover UI, (3) evaluation of information types and their presentation, and (4) potential for improvement.

15.4 Design, Development, and Demonstration

To construct a UI for the hybrid service recovery strategy with handover, pertinent theories and practical insights from experts are used to derive a set of MRs to allow optimization of continued interactions with customers after CA failure. We present corresponding DPs and their instantiation via DFs in a web-based prototype.

15.4.1 Meta-requirements

Theory-derived MRs. Seamless continuation of interactions with customers after CA failure requires a compilation and presentation of applicable information from the previous CA-customer interaction so that requests can be answered successfully without posing redundant questions. According to Cognitive Load Theory (CLT), the limited human cognitive capacity has to be considered to support individuals during information processing [56, 57]. Individuals' capability to handle task-relevant information can be promoted if the intrinsic, extraneous, and germane loads are balanced and do not overload human working memory [58]. Extraneous and germane load can be influenced by the presentation format [59]. As intrinsic load is high due to the complex requirements of real-time interaction, information should be presented in terms of volume and format that does not overload individuals' capacities to process (extraneous) and comprehend (germane) information. Therefore, the handover UI should comprise a limited amount of information (**MR1**) and present information in a way that supports comprehension building (**MR2**). After handover from CA to SE, the employee has to handle the customer request by executing problem-solving activities. For this purpose, actionable information is required. As the human ability to process information is restricted, problem-solving processes should be supported to limit the invested mental effort [60]. In this regard, Cognitive Fit Theory (CFT) postulates that individuals use information in the problem representation and task to create a mental representation of the problem, which allows them to produce a problem solution [61, 62]. The effectiveness of the problem-solving process can be influenced by the problem-solving task and problem representation. When the task and presentation of the problem match and help the individual to create a corresponding mental representation, problem-solving performance increases via improved accuracy and speed [61]. Accordingly, the handover UI should contain information that adequately represents the customer's problem or request so that SEs can generate a matching mental representation

(**MR3**). Besides the type of information, the presentation format is also relevant to support problem-solving behavior. In CFT, symbolic and spatial problem-solving tasks are differentiated. The first type refers to tasks that require the acquisition of discrete data and information to subsequently process via analytical thinking [61, 63]. In spatial tasks, relationships of data and information are established through associative thinking. To support individuals' problem-solving processes and enable them to create a fit between the presented and mental problem, the presentation format should match the task type at hand [63]. As the extraction of specific information is relevant after handover, information should be presented in a tabular format in the handover UI, so that SEs can easily interpret and process information (**MR4**).

Interview-derived MRs. The adoption of a handover UI to implement a hybrid service recovery strategy for CAs can lead to increased efficiency and effectiveness in continuing the customer encounter through time savings (E2-6) and improved quality in the interaction (E1, E3). To exploit the benefits of a handover UI, requirements in terms of the type and presentation of information should be fulfilled. For the continuation of an interaction, the questions "*what category, what product and what person, and what problem does the person have*" (E4) are essential. The indication of the customer issue and reason for CA failure is important to accurately determine the entry point for the conversation (E1, E3, E4, E6). Therefore, the specification of a request type (e.g., complaint), a summary or possibility to inspect the preceding CA-customer interaction, and overview of proposed solutions by the CA are required (E1-4, E6) (**MR5**). In addition, information about the customer and the object of request should be included: "*I would want to know - when the request is handed over - who this is and what is it about*" (E1). Therefore, information about the product and the customer's name are relevant to conduct a personalized interaction (E3-E5). For the presentation format of information, it is important to be able to "*extract all information at once, if possible at first glance*" (E5). The most important information should be presented in a way that allows quick processing and understanding to keep waiting time for customers short (E1, E3, E4). A prioritization in the arrangement of displayed information is helpful to instantly see the most important information with customer name, object of request, and customer concern (E1, E3, E5) (**MR6**). For conciseness, the amount of presented information should be limited and the possibility should be provided to display further details on request (E3, E4) (**MR7**). Furthermore, a "*structured visual presentation*" (E4) is useful. For this, there should be thematic categories with distances to each other (E3, E6), color differences (E4, E5) and tabular presentation of information with a "*gray-white-gray grid, so that you see rows for each theme*" (E1) (**MR8**). Apart from the presentation of information, the handover needs to be integrated into existing work processes of SEs. To implement handovers effectively, SEs should be informed in a way that minimizes work interruptions (E3-5). Ensuring sufficient preparation, the handover should be announced in advance (E3, E4) (**MR9**).

15.4.2 Design Principles and Instantiation

DPs. The identified MRs were used to derive three overarching DPs of the type form and function [64]. Based on kernel theories, four MRs emerged, while five were derived through expert interviews. Fig. 2 illustrates the mapping of MRs and DPs.

The presentation of information in a handover UI is a prerequisite for the continuation of the service encounter after CA failure. As humans have a limited capacity to process information, the set of information in a handover UI should be limited and more detailed information should be displayed on demand. Thereby, information processing can be supported and negative effects of overload can be avoided (**DP1**). To ensure a goal-directed request processing, information should be presented that allows SEs to quickly comprehend the problem and create a mental representation of it to answer the customer request. Therefore, the object and content of the request as well as identity of the requester should be displayed in a prominent manner (**DP2**). For effortless continuation of request processing after CA failure, information should be visually presented in a way that is easily processable and applicable to facilitate subsequent problem-solving activities of SEs (**DP3**).

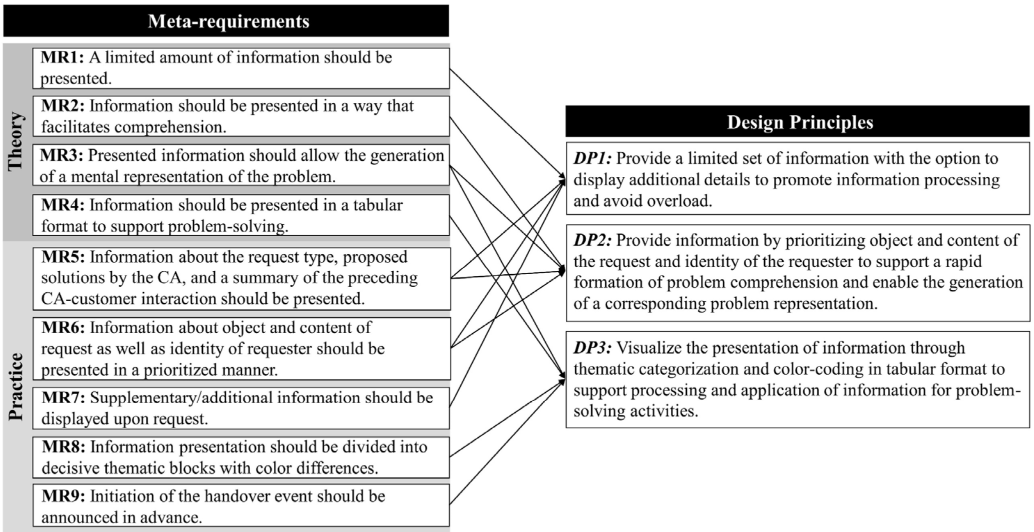

Figure 2. Derived DPs based on MRs

Prototype instantiation. The DPs were instantiated in a prototypical handover UI. To guide the development, DPs were translated into DFs to evaluate the web-based prototype with user tests (see Fig. 3). Once the handover has been initiated, the UI is populated with a limited set of information divided into thematic categories (customer, case, and product) (**DF1**: *DP1, 2, 3*) and presented in tabular format with different coloring (**DF2**: *DP2, 3*). Integrated detail-buttons are provided to display additional information for each thematic category (**DF3**: *DP1, 2*). To present inquirer identity, content and object of request, the customer's name, a summary of the previous CA-customer interaction, and product features are displayed (**DF4**: *DP2*) complementary to a chat history in the chat window. To announce an incoming customer interaction via handover, a status indication is presented with changing states (idle, 2 min., 1 min., start chat) (**DF5**: *DP3*). To minimize additional cognitive load and facilitate the use of provided information during customer interaction, the chat window is integrated into the prototype (**DF6**: *DP1*).

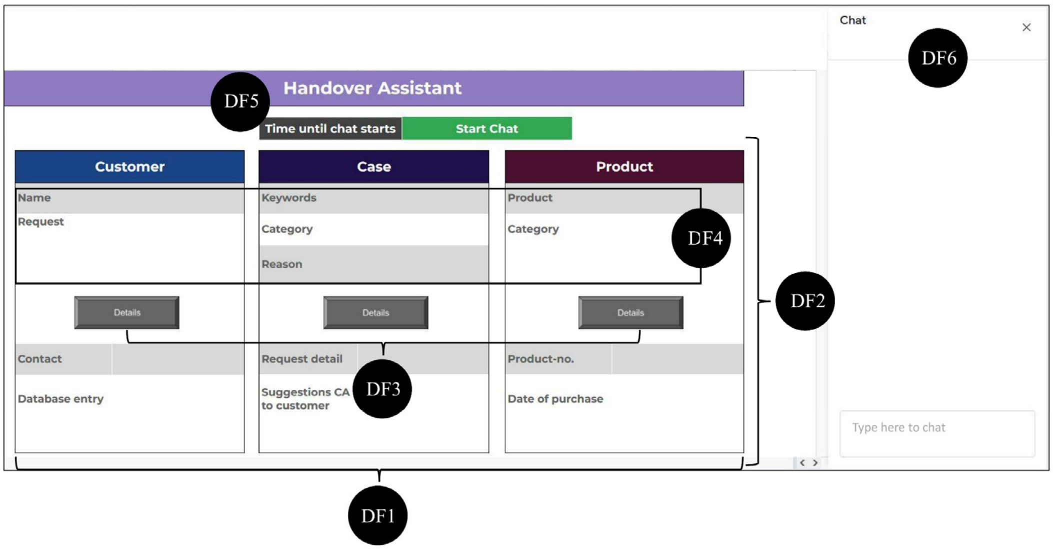

Figure 3. Web-based handover UI with DFs

15.5 Evaluation

The handover UI was evaluated with user tests to obtain insights into the usage behavior via screen recordings. In addition, interviews were conducted with ten PAs to assess the influence of the prototype on their behavior and task accomplishment. The analysis of usage behavior showed that PAs sent an initial message to the customer after on average 65 seconds. One-half (5/10) of the PAs sent a welcome message after on average 33 seconds, followed by a message with a question and/or problem-solving suggestion after another on average 30 seconds. The other half sent a combination of welcome message and question or solution proposal after on average 86 seconds. During the user tests, nine out of ten PAs used all three buttons to view more details. Eight PAs clicked the buttons after their initial message, whereas one person clicked the customer details button before the conversation started. Among these eight PAs, five generated a greeting and then a request-related message. Overall, eight out of ten PAs repeated questions previously asked by the CA. Of four CA questions, four PAs repeated one and four repeated two. All PAs proposed a suitable solution to the customer.

The analysis of the interviews revealed PAs' predominantly positive impression of the handover UI. The handling was rated as simple and presented information were conceived to be concise as they help to comprehend the customer request at hand (PA 1-4, PA6, PA7, PA9) (e.g., "*it is concise and short and not overstimulating, which is why you have a good overview*" (PA2)). The thematic differentiation of the presented information was evaluated positively, as it accentuates where to find which information and allows to determine what is needed (PA1, PA3-7, PA10): "*I also like the structure with these three fields and the* *overview as it helps to find one missing piece of information – I directly know in which part to look for it*" (PA1) and "*the structuring helps because I can easily filter what is important and what is not*" (PA7). However, the display of CA solution proposals as additional information in the category "Case" was criticized, as this information is important to understand the request and should therefore be visible immediately (PA1-4, PA6-10), e.g., "*I would prefer the suggestions 'chatbot to customer' at the top and not hidden in the detail, because this was the important information that was needed*" (PA6). Overall, the PAs considered the information to be relevant to continue the customer interaction. For problem solving, the category "Case" was rated as most important (PA1, PA2, PA4, PA5, PA8-10), because "[…] *information help to facilitate problem-solving, because I just know where it stopped*" (PA5). In addition to the "Case" summary comprising a category, keywords, and suggested solutions from CA to customer, information about the customer and product was rated to be useful. PAs reported that this information is valuable because no additional effort needs to be invested into collecting customer- or product-specific details. In addition, PAs directly knew how to address the customer, what the product is, and whether a warranty claim is valid (PA1-5, PA7-10). The need for a chat log as information was assessed differently by the PAs. Some preferred a chatlog to reassure themselves about the customer request (PA1, PA5, PA6, PA8) others relied on the summary in "Case" or prefer an optional display of the log (PA3, PA4, PA7, PA10).

For the continuation of the customer interaction, the use of the handover UI initially caused mental effort for the PAs, as displayed information had to be processed and contextualized. Subsequently, the processing of the request became easier (PA2, PA4, PA5, PA6, PA8, PA10), e.g., "*the interface is more complicated at first because I had to understand the interface and you had to figure out where to get what information. And then easier, because I knew where I was and how to proceed*" (PA8). The PAs expressed that request processing without the UI would be more complex and strenuous, as they would have been required to obtain information and evaluate it during customer interaction (PA2, PA4, PA5, PA6, PA8, PA10). In addition, PAs assume that mental demands and errors in the form of repeated questions are reduced by regularly using the handover UI (PA1, PA3, PA4, PA10). The continuation of the customer interaction was quick and goal-directed for the PAs because the initiation of the conversation was facilitated. PAs did not uniformly feel time pressure. For those who experienced it, the interface had a stress-reducing effect (PA1, PA4, PA10). As required information was presented, PAs were able to invest into individualizing customer interaction (e.g., addressing customer by name) (PA2, PA4, PA9). In general, PAs reported that using the handover UI reduced their invested time and workload (PA1, PA3, PA4, PA5, PA10): "*I see advantages in the fact that it reduces time, i.e., it reduces the workload, because you get information about what has previously been asked*" (PA10).

In addition to these findings, the user tests revealed potential for improvement. The continuation of the customer interaction could be improved, if the display of CA solution steps during customer interaction before handover was improved and directly visible (PA1-

4, PA6-10). Furthermore, information on customer sentiment either via viewable chatlog or integrated dashboard would be helpful to prepare for the interaction (PA6, PA9). The start of a customer interaction after handover should be determinable by the PA via a button (PA5, PA6, PA9). During interaction, canned responses (e.g., greeting messages) and suggestions for solutions could be useful to speed up problem-solving of PAs (PA6, PA9, PA2).

15.6 Discussion

In this study, we report on the development of DPs for a handover UI to avert CA failure in OCS and implement a hybrid service recovery strategy. As part of a larger DSR project, design knowledge from the first cycle on the handover process, collection, and transfer of information is supplemented with aspects of designing a UI in the current cycle that enables SEs to continue customer encounters quickly and effortlessly after CA failure. To answer the RQs, we derived three DPs based on practical requirements and theoretical findings and instantiated them in a web-based prototype for evaluation. The conducted user tests showed that the handover UI allows PAs to continue the customer interaction in a goal-directed fashion with limited effort. Therefore, the results suggest that, consistent with CLT, extrinsic cognitive load induced by the amount of presented information was manageable for SEs [56, 59]. The qualitative interviews with PAs revealed that the presented information types are relevant and allowed them to quickly generate an understanding of the problem due to the concise overview (DP1). This perception of the PAs indicates that the tabular presentation of the information in the three thematic categories according to CFT facilitated the quick formation of a mental representation of the problem, i.e., customer request [60, 62]. The importance of the summarized customer concern ("Case") for a seamless continuation of the interaction highlights the relevance of DP2. The integration of design elements (headings, colors, boxes) enabled PAs to easily find and process relevant information (DP3). The partial information display was used by the PAs to initiate the customer interaction promptly after the handover to subsequently view and analyze further details via the buttons. This approach was confirmed by the behavioral analysis based on the screen recordings, which showed that the optional details allow PAs to apply different strategies to start the interaction (greeting vs. greeting and problem-relevant message). However, the hidden display of CA suggestions to customer was obstructive for PAs, as the information remained undetected and customers had to answer redundant questions after handover. The evaluation results indicate that PAs have to invest a limited amount of time to initiate the conversation with the customer due to the handover UI and their workload is reduced. Furthermore, it lowers perceived time pressure and thus enables more customer-centric interactions. Last, the results suggest that benefits from using the UI unfold after repeated use and presupposes SEs' knowledge about the objects of request.

With this study we present a feasible way to advance the hybridization of online customer service. By interlocking CA and SE work processes via handover UI, CA failure can be prevented, SEs can be supported during service recovery, and customers quickly receive a solution. Hence, by presenting DPs and evaluation results, we provide contributions to research and practice. With the prescriptive design knowledge about form and function and explanatory knowledge about effects [55, 65, 66], we contribute insights to address knowledge gaps related to service recovery strategies for AI-based service delivery by incorporating theoretical insights referring to human cognitive functioning to design UIs [14, 21, 40]. Furthermore, we present a designed entity in form of a web-based handover UI, which represents a situational instantiation of our design. Thereby, we deliver guidelines on how to implement an immediate assistance recovery strategy in OCS. In addition, we present a potential solution to advance the hybridization of online service delivery by purposefully combining the strengths of AI and SEs. In practice, the design knowledge can be applied by service companies to implement a hybrid service recovery strategy to avert customer dissatisfaction in the event of CA failure and adequately support SEs to quickly generate a solution after handover.

Despite the promising findings, however, there are a few limitations to consider. The handover UI was artificially evaluated and customers simulated. In addition, the customer request was prepared for the evaluation to allow the involvement of participants from different online service contexts. These aspects limit the generalizability of presented results. Therefore, we propose avenues for future research. In a quantitative-experimental study, time advantages and quality of suggestions of different handover UIs could be compared to a baseline. In this context, the functionality of the UI could be extended by displaying appropriate knowledge items and/or canned responses (e.g., greeting messages) as a complement to the information from the CA customer interaction to support SEs during problem solving. In addition, the hybrid service recovery strategy for CAs could be implemented in an organization to measure (1) SEs' cognitive load induced by handover UI, (2) customers' satisfaction, and (3) operational efficiency in an OCS department with a quantitative longitudinal evaluation setting.

15.7 Acknowledgement

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16 Let's Team Up with AI! Toward a Hybrid Intelligence System for Online Customer Service

Poser, M., Wiethof, C., Banerjee, D., Subramanian, V. S., Paucar, R., & Bittner, E. A. C. (2022). Let's Team Up with AI! Toward a Hybrid Intelligence System for Online Customer Service. In A. Drechsler, A. Gerber, & A. Hevner (Eds.), Lecture Notes in Computer Science. The Transdisciplinary Reach of Design Science Research (Vol. 13229, pp. 142–153). Springer International Publishing. https://doi.org/10.1007/978-3-031-06516-3_11

Abstract
Customers desire convenient, fast, and personalized service encounters. Hence, service companies deploy self-service technology for online custom-er service. However, as solutions based on Artificial Intelligence cannot reliably answer the full range of requests and the demands on service employees (SEs) in live chat interaction are high, Hybrid Intelligence Systems (HIS) provide great potential to overcome current pitfalls by combining the complementary strengths of artificial and human intelligence. To ensure optimal performance of this socio-technical ensemble, human-centered design approaches are needed to realize real-time augmentation of decision-making in chat-based service encounters. Following a Design Science Research approach, we generate theory-based design principles (DPs) and implement them in a web-based HIS prototype. We contribute to Hybrid Intelligence re-search with results showing that the DPs enable task mastery and decision efficiency and provide avenues for future research.

Keywords: Hybrid Intelligence System, Real-time Decision, Customer Service

16.1 Introduction

Striving for operational efficiency, companies across various industries deploy automation technology enabled by Artificial Intelligence (AI) to process the ever-increasing number of requests in customer service [1, 2]. This development is expected to culminate by 2025 with 95% of all customer encounters being processed by AI [3]. Thereby, companies can increase their availability to customers, especially via online customer service (OCS) channels [4]. However, so far, full automation of online service interactions is not feasible, as narrow AI is not capable of handling all types of customer requests. Hence, strategies are needed to process the full range of customer requests while avoiding overload of service employees (SEs). In this context, research and practice postulate augmentation approaches relying on close collaboration between humans and AI to execute tasks [1, 5]. For real-time service encounters in OCS, the combination of AI's capabilities to rapidly process textual input and provide suitable decision suggestions [6] with SEs' ability to understand semantically complex content and handle unforeseen situations, can lead to effective customer request handling with in-creased decision-making efficiency. This augmentation approach can serve to meet customers' growing demand for personalized service encounters via text-based channels [7, 8]. In addition, real-time decision augmentation, e.g., displaying suitable information, can help SEs to rapidly process requests with increasing variability in content [9, 10].

In organizational contexts, the focal concept for augmentation strategies is Hybrid Intelligence (HI), which proposes the integration of the complementary strengths of humans and AI in a Hybrid Intelligence System (HIS) for joint task execution involving hybrid decision-making and hybrid learning [11]. To lever-age associated potentials of a HIS, human-computer interaction (HCI) needs to be designed concerning suitable input and output formats while meeting human needs for task mastery [12, 13]. However, so far, socio-technical approaches to design the collaboration between AI and humans for hybrid decision-making are under-researched [14, 15]. Thus, human-centered design approaches for AI are needed for the decision-making augmentation of text-based, real-time service encounters in HIS enabling optimized task performance and hybrid learning [12]. To address these knowledge gaps, we adopt the Self-Determination Theory (SDT) to select suitable psychological constructs, ensuring the fulfillment of SEs' needs. Accordingly, we pursue the following research question: *How should a HIS be designed in a human-centered way to augment real-time decision-making for online customer service encounters?* The goal is to enable augmentation in a HIS to sustain SEs' task mastery, efficient decision-making in service encounters and simultaneously meet the requirements for hybrid learning. With this study, we present the second cycle of a larger design science research (DSR) project with the following structure. First, we present the conceptual background. Second, we outline the research approach by describing the cycles and steps of the DSR project. Third, the derived meta-requirements (MRs) and design principles (DPs) are presented and the instantiation illustrated. Last, we present evaluation results followed by a discussion and conclusion.

16.2 Conceptual Background

OCS constitutes a pervasive form to deliver intangible services mediated via technology [2]. To meet customer needs, service is directed toward people or objects [16]. This service is knowledge-intensive, as SEs need to handle an in-creasing plethora of diverse content from explicit (e.g., data) to meta-knowledge (e.g., advice) to make multiple decisions during request processing [9]. In OCS, AI can enable flexibility in the external (frontstage) and support in the internal (backend) environment to deliver service [17]. However, the automation of frontstage encounters reduces the success-generating characteristics of social presence and personalization [8, 18]. To overcome this tendency, AI-enabled agents are designed in a human-like fashion to handle repetitive, simple requests via natural language interaction [19]. Nevertheless, these AI solutions have yet to create satisfactory customer experiences for complex, emotional requests. To achieve improved organizational and individual outcomes, the competencies of AI and SEs are increasingly integrated [6, 20]. In this context, the concept of HI is adopted to combine the complementary strengths of AI and humans [11] involving augmentation and hybrid learning leading to better results than each of the entities could reach alone [21]. For service encounters, [2] propose the augmentation of SEs invisibly to the customer during real-time interaction, to leverage advantageous conditions for service co-creation with high synchrony of communication as well as personal support [8, 22]. For this augmentation scenario, high demands in the form of instant knowledge retrieval for dynamic decision situations and emotion work should be met [9, 23]. Therefore, AI and SE can take over different roles: AI can provide analytical insights into the customers' requests (e.g., solution proposal) and the SE contributes intuition by contextualizing this information and leading an empathic interaction with a customer [4].

To ensure the success of HIS, conditions for a high degree of SEs' task mastery should be established during customer interaction. Thus, according to the Self-Determination Theory (SDT), augmentation should fulfill human desires for **autonomy**, **competence**, and **relatedness** [24]. SEs should experience the feeling of control over their behavior and make decisions independent of external conditions, as **autonomy** promotes the intensity of post-adoption usage behavior, engagement, and satisfaction with information systems (IS) [25, 26]. In addition, SEs should be able to actively interact with the environment to achieve desired results. By experiencing this **competence** using IS, SEs' self-efficacy could be elevated and decision efficiency increased [27]. Moreover, building a relationship (**relatedness**) with IS due to their social characteristics could influence SEs' perceived usefulness of and intention to reuse the technology [28, 29]. As the consideration of human psychological demands for the design of HIS is scarce, we utilize SDT to select suitable theories that help to meet the three basic needs of SEs in OCS. To promote SEs' autonomy and competence in dynamic customer interactions with a variety of interdependent decisions [9], we adopt the Dynamic Decision Theory (DDT) to support decision-making strategies [30]. Regarding Cognitive Load Theory (CLT) [31, 32], we integrate insights on the nature of information presentation, as decision suggestions should be designed considering their load on SEs' working memory due to intrinsic, extraneous, and germane factors. Following Advice Response Theory (ART) [33], the characteristics of advice have an impact on perceived quality. Therefore, to influence competence, the aspects of efficacy, and feasibility, and absence of limitations are considered for decision suggestions. To establish relatedness in a HIS, we consider Social Response Theory (SRT) [34], which states that the use of social cues in IS has relationship-enhancing effects.

16.3 Research Approach

To establish a human-centered design of HIS for organizational augmentation endeavors, we conduct a multicyclic DSR project. By adopting the interior mode of DSR, we (1) define and evaluate prescriptive design knowledge to "construct a HCI artifact for a given problem space" [35, p. 4] and (2) present a designed HIS artifact [36]. To ensure research rigor, we structure our project by applying the process model of [37] (see Fig. 1). In two design cycles, we incrementally identify MRs as goal and boundary descriptions of an artifact and derive DPs providing prescriptive statements [38–40].

DSR Research Cycle	**Cycle one:** Hybrid collaborative learning	**Cycle two:** Real-time AI-based decision-making augmentation
(1) Awareness of Problem	Integrate human and artificial intelligence in online customer service	Refinement and extension of problem relevance
(2) Suggestion	Derivation of MRs for hybrid collaborative learning	Derivation of MRs based on kernel theories for real-time decision-making augmentation
(3) Development	Definition of DPs and instantiation in web-based prototype	Extension of DPs and instantiation in full-featured web-based artifact
(4) Evaluation	Artificial evaluation (wizard-of-oz) of design with mixed-method approach	Semi naturalistic evaluation of design with mixed-method approach
(5) Conclusion	Codification of design knowledge as contribution to body of knowledge [currently under review]	Report, embed and contribute design knowledge about artifact's construction and effects

Figure 1. DSR approach based on [37] with research activities

To ensure validity in addressing the identified problem, we iteratively instantiate and evaluate the design of our HIS artifact in an organization that specializes in selling traineeships and projects abroad to customers. To address this real-world use case, the HIS is supposed to augment the processing of customer questions and identification of their interests (where, when, what) and the recommendation of suitable projects. To do so, in the first cycle [41], we derived theory- and practice-based MRs to define initial DPs for reciprocal augmentation through hybrid collaborative learning. This mutual learning scenario improves the performance of AI by SE experts as well as expands novice SEs' knowledge by AI. As a proof-of-concept, the tentative DPs were implemented in a web-based prototype with a user interface (UI). By conducting a wizard-of-oz study, the instantiated design and expected learning effects for novice SEs could be demonstrated. In the second cycle, covered in this paper, the design is extended and integrated with aspects for real-time decision-making augmentation to fully address the problem of this DSR project. In **(1) Awareness of Problem** (see Sections 1 and 2), we reassessed and elaborated on the problem relevance and need for a solution that integrates hybrid learning and real-time decision augmentation. For **(2) Suggestion**, MRs for real-time augmentation for decision-making are derived based on kernel theories (see Section 4.1) [36]. In **(3) Development**, DPs and matching design features (DFs) are determined to construct a full-featured AI-based HIS prototype (see Section 4.2) as an expository instantiation. For **(4) Evaluation** (see Section 5), following the risk and efficacy strategy [42], the prototype is implemented to conduct an online field study with 18 SEs (ten male, eight female) from the described organization. The study follows a standardized procedure: (1) the setting and prototype are presented; (2) participants use the artifact to counsel a customer while sharing their screen; (3) a semi-structured interview is conducted. As the customers are simulated by the research team, the evaluation is semi-naturalistic. By using three prepared customer profiles with scripts comprising question-and-answer variations, originality of interactions is ensured. To evaluate the designed artifact in terms of its applicability, feasibility, and effect on users, a multi-method approach is applied. The qualitative interview is structured with questions about demographic data, decision-making, trust in and satisfaction with the prototype, and changed task characteristics. In addition, quantitative measures of usage behavior were obtained from screen recordings (e.g., frequency of used functionalities). To analyze the rich data, a qualitative content analysis of the interview transcripts according to [43] is conducted, and descriptive statistical methods are applied for the assessment of the quantitative usage data.

16.4 Design and Development

16.4.1 Theory-derived Meta Requirements

Autonomy and competence. Following DDT [30], SEs apply strategies to make interdependent and real-time decisions in response to dynamic customer interactions [44]. Under time pressure, individuals make decisions by comparing information of options based on assigned values to identify an alternative with the greatest utility [45, 46]. Therefore, multiple suggestions should be proposed (*MR1*), presented in sequence allowing SEs to view alternating combinations (*MR2*) with relevant utility information (*MR3*). To promote comparability, suggestions should be displayed in descending order with respect to utility (*MR4*). The AI settings should be adjustable (*MR5*) to sustain autonomy. Besides facilitating decision-making strategies, the nature of information presentation has to be considered, as it affects SEs' processing ability [47, 48]. According to CLT, dynamic decision-making induces a high intrinsic cognitive load in SEs due to the necessity of monitoring the changing customer demands to make punctual decisions [49]. As this task occupies a significant portion of SEs' capacity, a low load of presented information (extraneous cognitive load) is required [32, 45]. By presenting information in a concentrated format, SEs' information comprehension can be improved [50, 51]. Hence, a limited number of suggestions should be displayed (*MR6*) according to the pace of the changing environment (*MR7*) and their effortless utilization facilitated (*MR8*) to avoid cognitive overload. In addition, characteristics of presented information impact decision-making [48]. Following ART, SEs' high rating of advice quality facilitates their decision-making, whereas discrepancies in expected and provided advice quality impede decision support [52]. To establish efficacy, the applicability and effectiveness of advice to solve a problem have to be present [48]. The quality of advice can also be enhanced by its distinctive workability (feasibility) and presentation of limited risks after its enactment (absence of limitation) [52]. Followingly, insights on the effectiveness should be provided by revealing the context-specificity of suggestions (*MR9*). The applicability and workability should be established by presenting explanatory information for suggestions (*MR10*). Reliability of suggestions should be provided to demonstrate the absence of limitations (*MR11*).

Relatedness. Advice-related decisions are also influenced by relational aspects such as respecting the autonomy of the decision-maker [53]. SRT postulates that social attributes promote a sense of social presence in users and have a positive effect on the intention to reuse, enjoyment of using, and self-efficacy in use [28, 29, 54]. Consequently, the appearance of and interaction with the AI should elicit a sense of social presence by mimicking human sociability (*MR12*) to promote the establishment of a relationship.

16.4.2 Design Principles, Design Features, and Instantiation

We present eleven DPs of the type form and function from two design cycles (see Fig 2) [55]. In the **first cycle**, seven DPs were identified for hybrid collaborative learning, which combines the augmentation of both human intelligence through AI and AI through human intelligence [11, 56]. To enable this, the HIS should include customizable settings so that SEs can individually determine whether the AI learns from them (**DP1.1**). Furthermore, the AI should be equipped with a social identity so that SEs perceive it as a collaboration partner (**DP1.2**). As instructional support, the HIS UI should include explanations of how the AI works to increase SEs' understanding of how to use it (**DP1.3**). For hybrid learning, the process and progress of the task should be observable (**DP1.4**) and an opportunity for AI and SE to share knowledge for decisions should be provided (**DP1.5**). To allow AI learning, an option for SEs to use or adapt AI suggestions (**DP1.6**) and the possibility to feedback the AI should be provided (**DP1.7**).

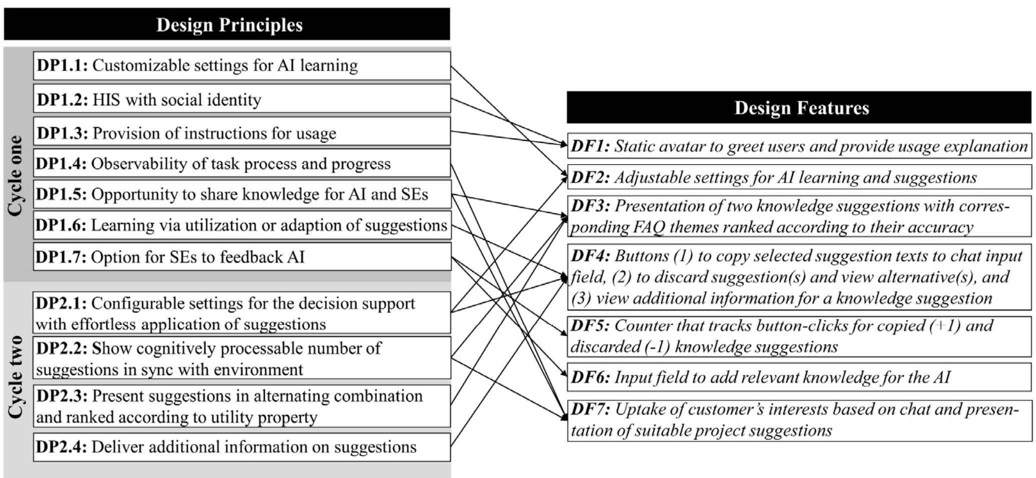

Figure 2. DPs of cycles one and two with DFs

In the **second cycle**, four additional DPs were generated to allow real-time decision-making augmentation. Thus, the HIS should provide configurable AI settings and the possibility to easily use suggestions to increase SEs' task mastery (**DP2.1**: *MR5,8*). A manageable number of context-specific suggestions in sync with the dynamic interaction should be displayed to augment SEs' decision-making (**DP2.2**: *MR1,6,7*). To support SEs' strategies for decision making, suggestions should be shown in sequence according to their utility and allow the display of alternating combinations upon request (**DP2.3**: *MR2,3,4,11*). Additional information about suggestions should be viewable so that SEs can verify their applicability (**DP2.4**: *MR9,10,11,12*).

Based on DFs, we instantiated these DPs in a web-based HIS prototype comprising frontend and backend (see Fig. 3). The web-based frontend was designed with Bootstrap and ReactJS to, inter alia, greet users with an avatar that presents a brief usage explanation (**DF1**). In addition, setting options for AI support and learning behavior are provided (**DF2**). The integrated chat window is based on the open-source framework Rocket.Chat. The backend generates a ranked list of FAQ suggestions based on chat interactions using Dense Passage Retrieval (DPR) technology [57]. The DPR model was pre-trained on the Google Natural Questions dataset by Facebook and further fine-tuned with conversational data from test runs. In the frontend, two FAQ items - including theme and accuracy in percent - with the highest agreement are displayed (**DF3**). The discard-buttons can be used to sequentially display four additional FAQ suggestions with decreasing accuracy. The copy-to-chat buttons insert FAQ text into the input field of the chat window. Detailed information about a respective FAQ can be viewed via the get-more-info button (**DF4**). With a counter, points are added (copy-to-chat) or subtracted (discard), if buttons are clicked (**DF5**). A feedback field allows entering search terms to select and submit a FAQ that matches the interaction (**DF6**). Based on customers' chat messages, exact keyword-based text matching is performed to automatically record interests and suggest suitable projects from a database (**DF7**).

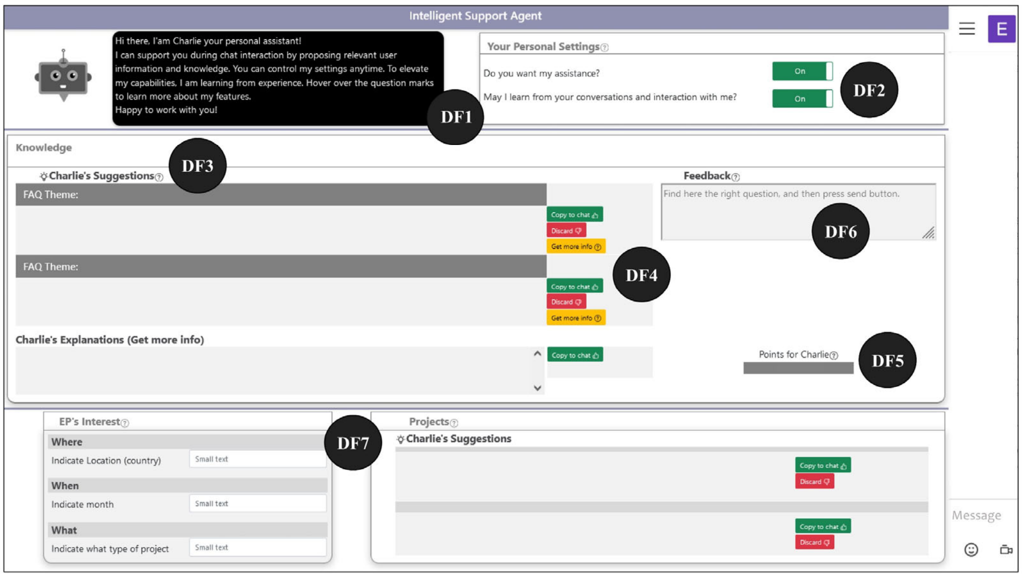

Figure 3. Screenshots of web-based HIS prototype with DFs

16.5 Evaluation

To evaluate the augmentation with the HIS prototype and its influence on the work task, we conducted interviews with 18 SEs after usage. Additionally, we inspected their usage behavior via screen recordings to supplement the qualitative results. Overall, SEs indicated that they would continue to use the prototype and highlighted that it is particularly helpful for SEs who do not have much experience in counseling customers.

DF1. The feeling of relatedness did not emerge consistently, as some SEs perceived the prototype as a tool and others as a co-customer manager ("*he definitely was co-customer manager because he gave me all the prompts to answer questions*" (SE13)). **DF2.** The analysis of screen recordings revealed that all SEs approved of support by the prototype and 12 consented that their data can be used for AI learning via the settings. **DF3.** During customer interactions, SEs sent on average 16 (*SD*: 5; *Median*: 14) messages during the customer interaction. 17 SEs used the FAQ answer suggestions via the copy-to-chat-button at least three times. On average, SEs edited two (*SD*: 2; *Median*: 2) of the suggested responses in the input field before sending them. The analysis of interview transcripts revealed that SEs were satisfied with the support provided by the prototype, as the provided suggestions appeared promptly, and the interaction was intuitive due to the functionalities and layout of the interface. Regarding customer interaction, SEs felt supported in their decision-making by provided suggestions, as the information allowed them to reassure themselves: "*it is a good thing to know what is going on and what could I answer, what are possibilities and what should I focus on. Also finding out the main point of the question of this customer*" (SE5). The decision- making was further supported by the trustworthiness of suggestions (e.g., SE17: "*in 80% of the times it was the right answer, so for me that is trustworthy*"). Their correctness was reported to be verifiable *"[...] when I pressed the get more information button, I could see what exactly was meant*" (SE4). Moreover, "*suggestions gave more time to think and then go into detail*" (SE3). However, some SEs experienced delays or hesitation when suggestions did not match the interaction: "*[...] that made the speed of me answering the question a little bit slower because I had to look for the answers myself*" (SE13). Also, proposals should be adjusted in wording and capitalized to simplify their use. Regarding customer interactions, SEs reported that they were able to autonomously manage them with provided suggestions (e.g., "*If I wanted to bring the conversation in another direction, I would have done it - so it was not forced*" (SE11)) and make independent decisions without feeling constrained (the prototype "*[...] is presented in a way that it was clear that I can work with him, but I don't have to"* (SE15)). In addition, the prototype assisted them to achieve their goals in counseling the customer: e.g., "*I was able to control the interaction. And I think the counseling was actually better because of Charlie's help because he explained things way more detailed than I would have done*" (SE15). However, SEs reported that the personal touch is reduced due to the provided wording in suggestions. **DF4.** Overall, an average of six (*SD*: 2.5; *Median*: 7) suggestions were used, whereby the detailed version via get-more-info button (*Mean*: 3.7; *SD*: 2.6;

Median: 4.5) was used more frequently than the short version (*Mean*: 2.6; *SD*: 2.4; *Median*: 2). To receive alternative FAQ answer suggestions, the discard-button was clicked on average 15 times (*SD*: 10.8; *Median*: 15). The display of two suggestions and the option for additional explanatory information via the get-more-info-button were perceived as helpful "*so that you can think in which direction you might go*" (SE1). SEs experienced relief through displayed suggestions and the majority saved time making decisions, especially by using the copy-to-chat-button: "*[...] I just had to copy them, which affected the speed*" (SE14). **DF5 & DF6.** 16 SEs utilized the feedback function on average four times, while nine people successfully provided feedback. However, SEs expressed the need for an adaptation of the feedback function, as it was unclear. **DF7.** Concerning the recommendation of projects, the pressure to recall knowledge or search in parallel to the customer interaction was reduced as relevant information was presented. Thereby, it *"[...] took out the uncomfortable part of working with such a consultation, which is looking up stuff*" (SE16).

16.6 Discussion and Conclusion

Our multi-cycle DSR project contributes to HI research [11, 21] by taking a human-centered perspective to design HIS [12, 13] for text-based, real-time service encounters [2] in OCS for mutual augmentation [15]. Particularly, we examine hybrid decision-making and hybrid learning. While we cover the enablement of hybrid learning in the first cycle, we extend this initial design in the second cycle to sustain hybrid real-time decision-making. To address our research question, we derived four additional DPs by considering relevant theories to define requirements that satisfy SEs' need for autonomy, competence, and relatedness. Based on the evaluation, the instantiated DPs successfully supported SEs' autonomy and task mastery in conducting customer interactions allowing efficient and independent decision-making. The SEs' feeling of control is supported by the analysis of screen recordings which showed that all SEs used the configurable settings to approve augmentation by the prototype (DP2.1). However, the evaluation revealed a high reliance of the SEs on the suggestions (DP2.2) partly leading to uncertainty and delays. Although SEs could conduct the service encounter without AI augmentation, they rather clicked the discard-button several times instead of formulating a new answer. In contrast, one SE only read and verified the suggestions and formulated new answers based on the provided content indicating a high level of SEs' autonomy. The need for competence could be addressed by supporting SEs' achievement of counseling goals via suggestions. In this regard, DP2.2 and DP2.3 successfully supported the dynamic decision situation by showing relevant information. Furthermore, the analysis of SEs' usage behavior demonstrates an intuitive application of suggestions by using the copy-to chat button in effortless ways (DP2.1). With this, DP2.1 is the main contributor to experienced relief, time savings, and efficiency. Moreover, SEs particularly recognized the usefulness of the get-more-info button (DP2.4), which is supported by the screen recording results that showed SEs' preference for the detailed version of suggestions. Regarding the need for relatedness, the evaluation did not show consistent results, as some SEs perceived the prototype as a tool and others as a co-customer manager.

All in all, we provide relevant and promising results demonstrating a potential solution to integrate hybrid learning and real-time decision augmentation within a HIS. We thereby make a two-fold contribution. First, following [38], we present a nascent design theory with utility character by delivering a possible solution for the identified problem and demonstrating improvements in the application field [36]. This contribution has epistemological implications, as we present DPs about user activity and an artifact that links prescriptive knowledge about design and action with explanatory knowledge about effects [40, 55, 58]. Second, we present a designed entity by demonstrating a full-featured AI-based artifact, which represents one possible instantiation of our design [36, 40]. Besides the promising results, there are, however, a few limitations to consider. First, we conducted one semi-naturalistic evaluation episode with simulated customers without a pre-evaluation of the instantiated DPs. Second, we limited the implementation and application of our DPs to only one organization. Thus, future research should implement and evaluate our DPs in various naturalistic environments. In doing so, factors should be examined causing different usage behavior and decision-making effects. For instance, while copy-to-chat might increase efficiency, it might also decrease human attention and learning. Especially when trying to educate novice employees with such a tool, proper usage of the suggestions needs to be ensured. In addition, SEs' decisions should be investigated in terms of quality due to influences of heuristics or biased AI. At last, as the feedback function was not clear to several SEs, we call for future research on how to ensure valuable and continuous feedback toward the AI.

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17 Design and Evaluation of an Employee-Facing Conversational Agent in Online Customer Service

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Abstract

Conversational agents (CAs) are increasingly deployed to automate online customer service encounters. Hence, researchers and practitioners have so far predominantly addressed attributes and features of customer-facing CAs toward more efficient customer request processing. However, as CAs still regularly fail to answer complex issues, the concept of Hybrid Intelligence (HI) suggests combining artificial with human intelligence in a Hybrid Intelligence System to overcome the weaknesses of CAs and service employees (SEs) and promote their strengths leading to enhanced performance results and collaborative learning through mutual augmentation. Thus, following a Design Science Research approach, we formulate design principles (DPs) to develop an employee-facing CA for augmenting SEs simultaneously to their customer interaction. We implement a CA prototype and evaluate it with 21 participants in a user test. We found that the DPs were successfully implemented. Thereby, we contribute to practice, customer service, and HI research and provide avenues for future research.

Keywords: Conversational Agents, Augmentation, Customer Service, Hybrid Intelligence

17.1 Introduction

In recent years, companies are increasingly exploring the potential of infusing information technology (IT) into online customer service to improve operational efficiency (Bitner et al. 2000; Glushko and Nomorosa 2013). Following this trend, service providers in different domains (e.g., finance, e-commerce, IT) are deploying instant messaging platforms to enable customers to interact with service employees (SEs) in real-time via chat (McLean and Osei-Frimpong 2017; McLean and Wilson 2016). This enables the execution of engaging and personalized service encounters to support customers instantly and in an individualized manner (Canhoto and Clear 2020; Huang and Rust 2018; Wirtz et al. 2018).

To further increase operational efficiency of online customer service, conversational agents (CAs) powered by artificial intelligence (AI) are progressively deployed to automate frontstage interactions with customers (Følstad and Skjuve 2019). CAs are defined as intelligent software systems that interact with users through spoken (e.g., voice-based assistants) or textual (e.g., chatbots) natural language (Bittner et al. 2019; McTear et al. 2016). Based on their analytical capabilities to quickly search large amounts of data, standardized customer requests can be processed reliably, which increases the accessibility and speed of companies' service delivery (Adam et al. 2021). However, CAs still have problems comprehending complex customer requests frequently causing service failure, which deteriorates service quality (Poser et al. 2021).

To prevent this common pitfall, augmentation strategies are currently being investigated to promote the strengths of AI and humans and compensate for the limitations of the other (Benbya et al. 2021; Jain et al. 2021; Østerlund et al. 2021). By combining their intelligences to a Hybrid Intelligence (HI), a Hybrid Intelligence System (HIS) enables AI and humans to achieve better results together than each could alone while ensuring continuous improvement through hybrid learning (Dellermann et al. 2019b; Dellermann et al. 2019a; Jain et al. 2021). Leveraging associated benefits, HIS have to be designed and developed addressing aspects of human-computer interaction to meet the requirements of input and output channels to facilitate hybrid task processing (Limerick et al. 2014; Pinhanez 2020; Rzepka and Berger 2018). With reference to research on AI, especially Machine Learning (ML), various interface modalities enabling human-computer interaction have been investigated (Amershi et al. 2014; Pinhanez 2020). For example, Dubey et al. (2020) developed a framework for human-AI collaboration to build a dashboard prototype with several AI-related functionalities to augment SEs' knowledge during customer interaction. Besides integrated AI solutions, CAs - representing AI-based agents - are another prominent class of interfaces for human-computer interaction (Glikson and Woolley 2020). Initial research has shown that CAs have a positive impact on employees' performance across various digital workplaces allowing intuitive dyadic, dialog-based interaction to receive output from information systems (IS) and to provide input and commands as well as feedback to improve the AI (Feng and Buxmann 2020; Meyer von Wolff et al. 2019b; Zheng et al. 2022). While capabilities of CAs have been extensively exploited in online customer service as customer-facing service channels, there is a lack of research on the design of employee-facing CAs to support human-human interaction (Hohenstein and Jung 2018; Meyer von Wolff et al. 2019a; Seering et al. 2019; Zheng et al. 2022). Referring to the concept of HI, combining human intelligence and AI can lead to superior results based on humans' intuitive capabilities, e.g., empathy, creativity, and flexibility and AI's analytical skills, e.g., consistency, speed, and efficiency (Dellermann et al. 2019b). Hence, augmenting the capabilities of either SE or CA through artificial or human intelligence respectively could advance SE-customer interaction (McLean and Osei-Frimpong 2017; McLean and Wilson 2016) as well as CA-customer interaction in chat-based service encounters in efficiency, speed, and individualization

(Adam et al. 2021; Følstad and Skjuve 2019; Janssen et al. 2020; Rapp et al. 2021). In terms of HI, mutual augmentation then ensures both the augmentation of the SE through the CA and vice versa. Therefore, addressing the described knowledge gap, we gather requirements and insights into the feasibility of a CA that presents information to and collects feedback from a SE in parallel to the SE-customer interaction. With the SE as the center of the CA-SE-customer interaction, we firstly focus on the augmentation of the SE while ensuring the augmentation of the CA. Consequently, we formulate the following research question (RQ):

RQ: *How can an employee-facing CA be designed and developed to augment SEs during customer interaction within HIS?*

To answer the research question, we design and develop a HIS for online customer service with a conversational interface. Therefore, the paper is structured as follows: In the Related Work, we present the conceptual background and the current state of research concerning CAs and HIS in online customer service. Subsequently, we introduce the Research Approach by outlining the Design Science Research (DSR) procedure and the applied methods. In Objectives of a Solution, we introduce meta-requirements (MRs) derived from literature and expert interviews. Thereafter, we define design principles (DPs) and describe their instantiation via design features (DFs) in a technical prototype. Next, the results of the evaluation of the implemented prototype via user test are presented. In the Discussion, we outline our findings, address the limitations of the study, and identify avenues for future research. The paper ends with a conclusion.

17.2 Related Work

17.2.1 CAs in Online Customer Service

With organizations increasingly adopting AI-based technologies, CAs particularly gained in popularity among both practitioners and researchers (Benbya et al. 2021; Klopfenstein et al. 2017; Schuetzler et al. 2021). Hence, research on CAs is widespread in the field of IS and can be conducted, organized, and grouped along various perspectives, e.g., tasks, application areas, and objectives (Meyer von Wolff et al. 2019a; Meyer von Wolff et al. 2019b). For a common understanding, we define CAs referring to Diederich et al. (2022, p. 4) as "technological artifacts with which users interact through natural language, both in written and spoken form". For our research, we limit the definition of CAs to their written form, as we specifically study CAs in the form of text-based chatbots. Eventually, CAs provide an alternative interface to graphical user interfaces (UIs) for accessing IS in a dialogical fashion via natural language (Feng and Buxmann 2020; Følstad and Brandtzaeg 2017; Følstad and Skjuve 2019; Klopfenstein et al. 2017). Hence, comprehensive research has been conducted to provide conceptual foundations, categories, design guidelines, and potential avenues for future research on CAs (Diederich et al. 2022; Feng and Buxmann

2020; Janssen et al. 2020; Meyer von Wolff et al. 2019a; Meyer von Wolff et al. 2019b). For instance, Janssen et al. (2020) established a taxonomy of design elements for domain-specific CAs along the perspectives of context, intelligence, and interaction. In terms of context, one prominent application domain is customer service (Diederich et al. 2022; Janssen et al. 2020; Meyer von Wolff et al. 2019a; Meyer von Wolff et al. 2019b). As organizations strive for automation, they exploit the potential of CAs to replace SEs with self-service solutions (Huang and Rust 2018; Meyer von Wolff et al. 2019b; Robinson et al. 2020), i.e., answering simple customer requests (Dwivedi et al. 2019; Xu et al. 2020) to provide instant customer support (Svenningsson and Faraon 2019). With this, organizations aim to increase their productivity covering efficiency and cost reduction (Brandtzaeg and Følstad 2017; Janssen et al. 2020; Meyer von Wolff et al. 2019a). Research on CAs in customer service predominantly focuses on this endeavor, i.e., the design and development of suitable customer-facing CAs, e.g., with social cues like language style or typing indicators (Gnewuch et al. 2017; Gnewuch et al. 2018; Gnewuch et al. 2020), empathy (Xu et al. 2017), human-likeness (Svenningsson and Faraon 2019), verbal anthropomorphic design (Adam et al. 2021), and considering task complexity as well as usage intention (Xu et al. 2020).

Despite research on advancing CA usage in customer service, CAs' ability to provide adequate service and support is of uttermost importance (Følstad and Skjuve 2019). However, as of now, technological advancements in AI have not yet reached a general intelligence to properly understand natural language in its full diversity. This impairs understanding and processing of, as well as reacting to customer requests and emotions, which leads to CA failure (Brandtzaeg and Følstad 2017; Dellermann et al. 2019b; Følstad and Skjuve 2019). Hence, researchers suggest involving SEs for request escalation through CA-SE handovers (Følstad and Skjuve 2019; Poser et al. 2021). While such handover scenarios enable a sequential combination of CA and SE, recent research disclosed a new perspective of combining both AI and SE's intelligence to process requests simultaneously through mutual augmentation (Keyser et al. 2019; Larivière et al. 2017; Poser et al. 2022b). The bold arrows in Figure 1 depict how this concept allows for (1) human-human interaction, i.e., SE-customer, while (2) AI augments the SE invisibly for the customer. However, as most research focuses on customer-facing CAs, there is a lack of research on employee-facing CAs (Meyer von Wolff et al. 2019a).

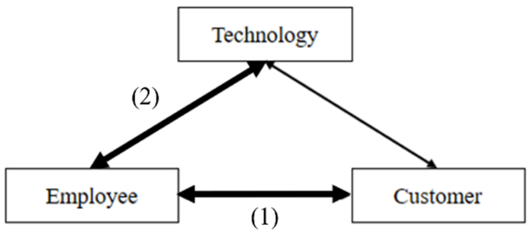

Figure 1. Frontline service technology infusion, augmentation scenario (Keyser et al. 2019), adapted

17.2.2 HIS in Online Customer Service

When it comes to augmentation of both artificial and human intelligence, researchers increasingly design and develop HIS as they “have the ability to accomplish complex goals by combining human and AI to collectively achieve superior results than each of them could have done in separation and continuously improve by learning from each other” (Dellermann et al. 2019a, p. 3). Thereby, HI specifies a collaboration between humans and machines, i.e., a task is collaboratively solved by humans and machines within a HIS (Dellermann et al. 2019a). Investigating collaborative agents as well as human-machine-teaming, the concept of HI emerged from research on human-machine-collaboration (Bittner et al. 2019; Norman 2017; Seeber et al. 2020; Strohmann et al. 2019; Wiethof et al. 2021; Yu et al. 2019). This concept focuses on mutual augmentation mechanisms toward artificial and human intelligence leading to better results and continuous collaborative learning (Dellermann et al. 2019b; Wiethof and Bittner 2021).

So far, AI is implemented through UI features in HIS, e.g., dashboards (Dubey et al. 2020; Poser et al. 2022a; Wiethof and Bittner 2022) in terms of dedicated applications (Følstad and Brandtzaeg 2017). Still, due to their intuitive and engaging nature, CA interfaces are likely to become the preferred UI (Følstad and Brandtzaeg 2017; Klopfenstein et al. 2017). Nevertheless, there is a lack of research on CA involvement in human-human conversation. For instance, while Feine et al. (2020a, 2020b) investigated CA development systems focusing on the development process through interaction between domain expert and CA, Gao and Jiang (2021) and Hohenstein and Jung (2018) provided starting points for HIS with an agent focusing on the human-human-interaction. Thereby, they examine, among others, usage, efficiency, and quality of suggestions provided by the CA. These insights provide a valuable starting point to extend the study of HIS with a CA. Accordingly, Gao and Jiang (2021) call for future research on the use and evaluation of domain-specific CAs in the context of real-world tasks and natural human-human interaction. In this context, valuable results could be obtained by ensuring the motivation and goal orientation of human participants (Brandtzaeg and Følstad 2017; Janssen et al. 2020). With our paper, we address the research gap on employee-facing CAs in online customer service and adopt findings from team research toward CA-SE collaboration. Based on this, we design a human-centered HIS with a conversational interface contributing to research on HI.

17.3 Research Approach

We adopt the DSR approach to develop a socio-technical solution for a prevalent real-world problem (Gregor and Hevner 2013; Hevner et al. 2004). To structure the process of generating prescriptive design knowledge in the form of DPs for the construction of a HIS with an employee-facing CA, we follow the six steps of the established DSR method of Peffers et al. (2007) (see Figure 2).

DSR Steps	Activities
(1) Problem Identification	Identification of research gap on employee-facing CAs to augment SEs during customer interaction
(2) Objectives of a Solution	Identification of MRs based on a SLR and expert interviews
(3) Design & Development	Derivation of DPs and development of an employee-facing CA
(4) Demonstration	Implementation of a CA prototype
(5) Evaluation	User test and mixed-method evaluation of CA prototype to provide a proof-of-concept
(6) Communication	This publication

Figure 2. Research Approach with DSR Steps

The first step refers to *Problem Identification*. By reviewing core publications in Sections 1 (Introduction) and 2 (Related Work), the current real-world challenge of companies was identified. Currently, organizations face the challenge to ensure an efficient application of AI-based CAs for interaction with customers in the online customer service frontstage by accommodating their current limitations.

As part of the second step, *Objectives of a Solution*, we utilized results of a structured literature search (SLR) according to Webster and Watson (2002) and vom Brocke et al. (2015). This SLR was conducted in the context of a preceding study about characteristics of AI in (online) customer service that are structured along the dimensions of (1) **service context**, (2) **capabilities**, (3) **deliverables**, (4) **integration**, and (5) **intelligence** (Poser et al. 2022b). Using these insights, we identified MRs that define the scope, capabilities, task types, and deliverables of an employee-facing CA. Furthermore, the appearance and behavior as well as the interaction with customers and SEs, and the intelligence (data basis and its processing) are determined. To supplement these literature-based MRs with insights from experts (E1-5) in the application domain, five semi-structured interviews according to Myers and Newman (2007) were conducted with SEs from one cooperating company.

For steps three and four (*Design and Development*; *Demonstration*), the previously identified MRs were used to define DPs. More precisely, following the taxonomy of Möller et al. (2020), supportive DPs were developed in one iteration based on the previously derived MRs. To this end, two researchers identified thematic commonalities across MRs and formulated materiality-and-action-oriented DPs according to Chandra et al. (2015). These DPs describe how the artifact should be produced and what it should contain. In addition, a data set for the development of the CA prototype was created based on frequently asked questions (FAQs) and matching answers from the cooperating company. To instantiate the DPs, DFs were defined to guide the development and situated implementation of the prototype.

In step five *Evaluation*, applying a mixed-method approach, the CA prototype was assessed. For a user test, 21 participants were recruited via a university email distribution list. The sample consists of individuals (five female, 16 male) between the ages of 18 and 40. Eight of these participants have pertinent work experience in customer service. 19 participants indicated that they do not have experience in using CAs or use them infrequently. The user test followed a standardized procedure. First, participants were introduced to the task and functionalities of the CA prototype by members of the research team. Second, participants engaged in a customer interaction to test the prototype. Third, following the user test, participants completed a questionnaire and participated in a semi-structured interview. In this semi-naturalistic evaluation setting, customer requests during the prototype test were simulated by the research team with predefined scripts. Utilizing an interview guide, participants were asked to assess the (1) applicability and completeness of the DPs, (2) usage characteristics, performance, and (3) impact of the CA on work practices. To supplement these qualitative data, a questionnaire was used to obtain insights on (1) perceived humanness, (2) perceived usefulness, and (3) continuance intention to use. Validated scales were used for this purpose. Perceived usefulness was measured with four items based on Davis (1989) with a 5-point Likert scale. Continuance intention to use was assessed with three items according to Bhattacherjee et al. (2008) with a 5-point Likert scale. Perceived humanness was measured with six items based on a 9-point semantic differential scale according to Holtgraves and Han (2007). In addition, quantitative measures of usage behavior (click and typing behavior) based on the usage logs, were collected and analyzed. As part of step six *Communication*, we present the activities of the described DSR steps in this paper.

17.4 Objectives of a Solution

The identification of MRs is guided by the concept of HI (Dellermann et al. 2019b; Dellermann et al. 2019a). By integrating an AI-based CA into online customer service, we strive to combine both artificial and human intelligence leading to mutual augmentation. In this hybrid collaboration scenario, an employee-facing CA, as UI of a HIS, represents an artificial teammate for SEs to conduct customer interactions. According to Social Response Theory, humans perceive computers with social cues as social actors (Nass and Moon 2000). As CAs have anthropomorphic characteristics, individuals unconsciously apply social rules and develop expectations toward human-like behavior of CAs in accordance with the social context (Araujo 2018; Feine et al. 2019). Serving the role of an artificial teammate, the employee-facing CA should therefore meet SEs' expectations toward humanoid team behavior (Poser and Bittner 2020). Therefore, to structure the derivation of MRs from literature and expert interviews, we use the established input-process-output model from team research. With this model, relevant capabilities, activities, and performance outcomes for hybrid collaboration between an employee-facing CA and a SE can be assigned based on the three dimensions. In this model, (I) **inputs** refer to the capabilities of involved agents to process a given task, (II) **processes** include activities performed by involved agents to achieve a joint task goal, and (III) **outputs** concern the evaluation of the team performance and fulfillment of team members' needs (Kozlowski and Bell 2006).

Inputs address capabilities that enable the CA to behave as an artificial teammate. To serve augmentation, the CA should be deployed in the frontstage to propose suitable response suggestions to the SE for customer requests (Dellermann et al. 2019a; Ostrom et al. 2019) (**MR1**). Depending on the use case, the CA should be able to suggest responses to simple, routine requests or more demanding problems involving the processing of data and information with or without the analysis of customers' emotions (Huang and Rust 2018; Wirtz et al. 2018). As the majority of requests are simple, the CA should provide support for these customer issues (E1-4). Hence, the CA should be able to at least process FAQs and deliver adequate responses (**MR2**). To do so, the CA has to be equipped with a database comprising a vast set of problem-solution pairs to provide suitable suggestions to the SE (Krogh 2018; Schuetzler et al. 2021) (**MR3**). To reliably identify corresponding answers to a request, the CA should be able to recognize customers' intentions irrespective of the phrasing (E5) (Følstad and Brandtzaeg 2017; Hill et al. 2015; Mallios and Bourbakis 2016) (**MR4**). Considering the nature of a HIS (Dellermann et al. 2019b; Dellermann et al. 2019a), the CA should allow SEs to provide feedback during interaction. Thereby, the CA can be augmented and the knowledge base can continuously evolve after a number of customer interaction sessions (**MR5**).

Processes refer to activities performed by the CA to collaborate with the SE to provide customer service, e.g., solving customer requests. For a hybrid handling of requests in the frontstage with the joint objective to answer customer questions, the goals of SE and CA should be aligned (Elshan and Ebel 2020; Nguyen et al. 2021) (**MR6**). As the SE is responsible for the execution and control of the customer interaction, the CA performs the subordinate goal to follow the chat-based, real-time interaction between SE and customer in order to suggest appropriate responses to the SE (E1-4). In doing so, the SE should perceive the availableness of the CA for interaction while allowing its monitoring of actions (Bulu 2012; Goel et al. 2013) (**MR7**). This form of support is helpful for SEs to perform the customer interaction (E1-4). Serving the augmentation role, the involvement of the CA should not be transparent to the customer, limiting the interaction to the SE (Ostrom et al. 2019; Robinson et al. 2020) (**MR8**). During performing the joint task of processing and solving customer requests, SE and CA have to establish a shared focus and mutual understanding via interacting with one another (Nguyen et al. 2021). To adapt augmentation to the conditions of a fast-paced, synchronous SE-customer interaction, the CA should behave reactively by displaying suggestions instantly and in sync with messages from the customer to avoid delays (McLean and Wilson 2016; Portela and Granell-Canut 2017; Song and Zinkhan 2008) (**MR9**). To provide the means to process requests in a goal-oriented fashion, the CA should present multiple response options that allow SEs to choose from but do not overwhelm them (E1) (Følstad and Taylor 2020) (**MR10**). In terms of SEs' effectiveness and efficiency to complete the task, i.e., resolving a customer request, the CA should allow SEs to effortlessly use and/or adapt the provided suggestions and provide feedback (Diederich et al. 2019) (**MR11**).

Outputs refer to requirements addressing the evaluation of the results of the hybrid team by customers. As customers overestimate waiting times leading to a negative service experience, the problem should be solved in short sessions by the hybrid team (Cheong et al. 2008; McLean and Osei-Frimpong 2017). In doing so, the quality of the answers should be adequate and fulfill the need of customers for an engaging and personalized service interaction (Canhoto and Clear 2020; Turel and Connelly 2013). In this context, empathy is important to build a relationship with the customer (Paluch and Wirtz 2020). To support SEs to comprehend the emotional situation and respond to the customer's needs, the CA should offer different tonality in response suggestions for the SE (Medhi Thies et al; Xu et al. 2020) (**MR12**). Given that the nature of hybrid collaboration is relevant in addition to the outcome, a natural interaction between CA and SE should be promoted to positively influence the continuance intention of CA use by SEs (Bhattacherjee 2008; Følstad and Brandtzaeg 2017). Therefore, the CA should be designed to be user-friendly (E3), engaging, and equipped with personality traits, e.g., an icon and name for the CA (E2) (Jenkins et al. 2007; Nass et al. 1994; Nass and Moon 2000) (**MR13**). For the establishment of a personal connection, the proposed suggestions should be introduced by short and understandable messages from the CA to the SE (Nguyen et al. 2021) (**MR14**).

17.5 Artifact Design, Development, and Demonstration

17.5.1 Artifact Design

To design and develop a HIS, we considered both humans (SEs as in online customer service) and AI (CAs as with conversational interface) for collaboration toward mutual augmentation (Dellermann et al. 2019b). Therefore, based on the 14 MRs, we derived five DPs that constitute prescriptive knowledge and define what aspects should be considered (design) and how (action) an employee-facing CA can be created for a HIS in online customer service (Gregor 2006; Gregor et al. 2020) (see Figure 3). Thereby, the DPs include distinct mechanisms involving SEs and CAs as enactors and/or users (Gregor et al. 2020). Following the framework of Wache et al. (2022), we present DPs that have a balanced level of abstraction and density of concepts.

The CA's capability in the form of processing incoming messages from the customer in terms of content and emotional tone is a relevant input for hybrid teamwork with the SE to propose appropriate response suggestions (**DP1**). An additional feature that is relevant in terms of a HIS allowing mutual augmentation and continuous learning is the ability of the CA to learn based on SE feedback for proposed responses (**DP2**). During the hybrid processing of a customer request, the CA, invisible to the customer, should follow the SE-customer interaction simultaneously. For the submission of suggestions, the CA should act reactively to only suggest answers for incoming customer messages, if suitable solutions are available. In terms of a positive service experience as an output of the hybrid teamwork between CA and SE, the SE should be facilitated to create a personalized interaction with the customer. Therefore, the CA should offer several response suggestions with different sentiment levels to match customers' emotional states (**DP3**). In addition, for effective hybrid teamwork, the CA should enable the SE to easily use and customize the suggested responses to support prompt reactions to customer questions (**DP4**). To enable satisfactory hybrid teamwork from the SE's perspective, the CA should establish a personal connection with the SE through a virtual identity and messages (**DP5**).

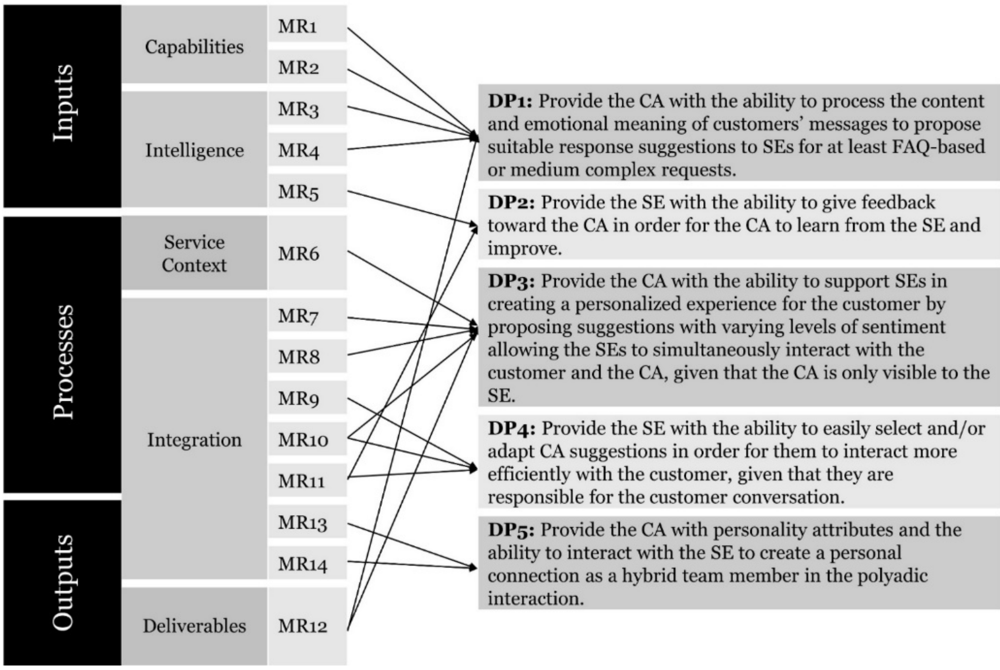

Figure 3. DPs based on MRs

17.5.2 Artifact Development and Demonstration

To create a situated instantiation of these DPs in the form of a technical proof-of-concept prototype, we defined a set of DFs. These DFs refer to attributes and capabilities of the artifact to address the DPs (Meth et al. 2015) (see Figure 4). To allow an effortless utilization, the CA is integrated into the customer chat window and displays a text message, visible only to the SE, with two response suggestions as an immediate reaction to a customer message, if a solution for the request is available. The suggestions have the same content with different wording: (1) neutral-factual and (2) personalized (**DF1:** *DP1, DP3*). To provide SEs with the means to effortlessly use one of the suggestions, the two response options each have a button function. Once a suggestion is clicked, it is directly sent as a message to the customer (**DF2:** *DP1, DP4*). The learning function of the CA is enabled by SE's selection behavior. A thumb-down button can be used as feedback for unsuitable suggestions. The use of an answer by clicking on it represents positive feedback for a suggested response (**DF3:** *DP2, DP4*). An integrated edit button allows the modification of suggested responses in the text entry field before sending (**DF4:** *DP1, DP4*). The CA prototype is presented with a virtual identity via an avatar and its name "Sam". Furthermore, the CA proposes suggestions along with a message to the SE (**DF5:** *DP3, DP5*).

The implementation of these DFs is illustrated in Figure 4. Before development, a decision between an ML-based and rule-based architecture was made based on the availability of data. As only a small number of problem-solution pairs to customer requests were available in the dataset from the cooperating company, a rule-based architecture was used to implement a proof-of-concept CA. This rule-based prototype allows better anticipation of the CA's behavior for the user test to prevent negative influences from ML that may not yet be ideal during the user test. To propose factual and personalized CA response suggestions, a database consisting of intents with predefined tags, recognition patterns as well as corresponding responses was created based on the FAQ. A web application was developed for the integration of the CA. To incorporate the CA into the application, the web framework Flask was used. HTML was utilized for the design of the graphical UI. During operation, input in the form of incoming messages of a customer is broken down into segments and processed according to specified rules and recognition patterns. To retrieve suitable responses, intents and response specifications are generated. The identified responses are then displayed in a message from the CA within the interface via Flask. If the input does not match the predefined recognition patterns, no action is performed.

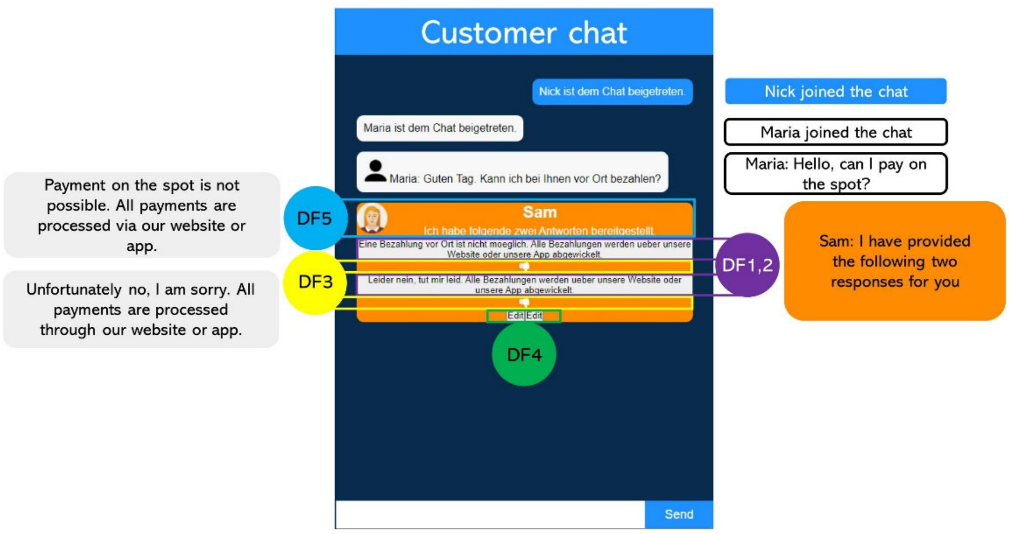

Figure 4. Web-based CA prototype with DFs

17.6 Evaluation

We assessed the deployment of an employee-facing CA augmenting SEs during customer interaction by conducting a user test with 21 participants (P1-21) (approximately 30 minutes each) and analyzed their usage logs, i.e., the interactions with the CA suggestions. To address the successful implementation of the DPs, we supplement the usage results with quantitative measures of perceived humanness, perceived usefulness, and continuance intention to use via questionnaires, and qualitative insights by conducting semi-structured interviews.

The usage logs comprise a total of 209 interactions each encompassing one customer question and the subsequent SE activities. 100 interactions show the usage of the CA's factual response suggestion while 90 reveal the usage of the CA's personalized response suggestion. Only eight response suggestions were edited, four of them personalized and four factual suggestions. The remaining 11 interactions show rejections of the suggestions, i.e., the answer was formulated without CA augmentation. Thus ~95 % of all interactions prove the successful usage of CA suggestions. Apart from that, the feedback functionality toward one suggestion was used in 25 interactions, 18 for factual and seven for personalized suggestions.

The usage log data give a first impression of the CA involvement in the customer interaction and SEs' usage of CA suggestions and thereby account for the successful implementation of the DPs. The analysis of the interview transcripts and questionnaire measures further complement the results with valuable insights as follows.

DP1: Participants like the response suggestions specifically due to their preciseness, as they are adequate, on point, and match the customer questions (P3, P7, P11, P13-15, P17-21). Derived from FAQs, the suggestions help to structure and align customer interactions (P13) as well as reduce errors (P8, P11, P19). As participants appreciate the CA for its fast access to all required information (P5, P6, P8, P10, P12, P14), its application for such a use case is considered meaningful and useful (P1, P14, P16).

DP2: The limited usage of the feedback functionality can, for one thing, be ascribed to a comprehension difficulty. More specifically, participants did not know what would happen when the button is clicked (P1, P2, P6). For another thing, it was criticized that there is only the option to explicitly give negative feedback but not positive feedback (P2, P12). Nevertheless, in general, a feedback functionality was judged to be a useful feature (P9, P15, P18, P21). To further improve the functionality, it is not only necessary to include the option to give positive feedback, but also to specify feedback (P15). This could be realized by giving access to data structures, e.g., the FAQ set (P15).

DP3: Although the response suggestion feature was highly appreciated by the participants, some responses should have been better formulated, e.g., they were lacking courtesy, were too casual, or too emotional (P4-6, P11, P12, P15, P16, P19-21). Thus, it was beneficial to have different options (P10, P11, P16-18). Still, participants recommended having more suggestions (P2, P7, P12, P16), e.g., at least a third option combining the more factual with the more personalized suggestion (P1, P15). However, some also wished for less redundancy as sometimes the response suggestions were very similar (P3, P8, P13-15). For further improvement, the CA should also provide adequate conversation beginnings and endings, e.g., greetings and goodbyes (P3, P4, P6, P11, P12, P19). At last, it was positively emphasized that the direct suggestions were provided fast and clearly (P9, P17, P18, P20, P21) allowing the SEs to simultaneously interact with the customer and the CA.

DP4: Due to its fast information processing and delivery pace, the CA increased the efficiency (P2, P3, P5, P6, P8, P10, P11, P13, P16, P19) and simplicity (P3-8, P10-15, P17-21) of work activities by allowing faster customer request processing (P1, P3-8, P11-21). This was further supported by the intuitive UI (P3-10, P12, P14, P15, P17-21) enabling an easy selection of the response suggestions (P2, P4, P10, P19) as well as an easy adaptation in terms of adding, emphasizing, individualizing, or personalizing responses (P1, P3, P6-8, P10, P11, P14, P15, P18, P19, P21). For improvement, the "edit" buttons could be better positioned, e.g., directly attached to each response suggestion (P1, P3, P7, P9, P10, P16, P17).

DP5: Regarding the perceived humanness of the CA, the analysis of questionnaire measures delivered mixed results (*Mean*: 6.67, *SD*: 1.56, *Median*: 7.00) that are supplemented by further evidence in the interview transcripts. While some reasoned for the CA's humanness, e.g., predominantly because of its language style and suggestions (P1, P3, P7, P8, P15, P18-21), the lack of appropriate greetings, goodbyes, and empathetic filler words as well as the limited response suggestions made the CA less human-like for others (P2, P5, P6, P12, P14). Nevertheless, none of the participants pointed out an impact of perceived humanness on their satisfaction with the CA.

Eventually, the high continuance intention to use (*Mean*: 3.87, *SD*: 1.13, *Median*: 4.00), based on satisfaction, and the perceived usefulness (*Mean*: 4.27, *SD*: 0.63, *Median*: 4.33) strongly prove the successful implementation of the DPs.

17.7 Discussion

The results of our work contribute to research in online customer service, HI, and employee-facing CAs by addressing hybrid teamwork between SE and CA. By investigating an employee-facing CA as an interface of a HIS, we present one possible way to create an augmentation scenario in the frontstage of online customer service. To this end, 14 MRs were identified based on findings from literature and practice to define five overarching DPs, whose implementation could provide employee-facing CAs with the capability to handle customer requests simultaneously to and as support for SEs as part of a HIS.

To gain insights into the applicability and completeness of our DPs, we developed a proof-of-concept CA. The deployment of this CA for a user test showed that the instantiated DPs supported participants in performing a customer interaction with provided response suggestions. This is reflected by the high number of utilized suggestions by participants (198 used out of 209 suggestions) and supported by their high usefulness rating of the CA along with a strong intention to work with it again in the future. With DP1 and DP4, the combination of the CA capabilities to propose suitable response suggestions and the opportunity for SEs to effortlessly use or adapt them, SEs are enabled to efficiently handle customer requests in real-time by utilizing the provided information probably causing fewer errors. The demonstrated usefulness of the CA's ability to quickly propose suggestions to the SE in sync with the customer interaction is consistent with research findings indicating that customers expect prompt responses in online customer service contexts (McLean and Osei-Frimpong 2017; McLean and Wilson 2016). Therefore, it is conceivable that SE's use of responses might have a positive effect on the customers' service experience. An additional factor that can contribute to this perception of customers is the adaptation of responses to their current situation (Canhoto and Clear 2020; Wirtz et al. 2018).

To individualize the interaction, DP3 addresses the proposal of different response suggestions by the CA in relation to the current level of sentiment of customer messages. The interview data suggest that participants perceived the provided number and content of responses to be beneficial. This finding is supported by the usage logs, which show that participants heavily relied on the suggestions using factual and personalized responses to the same extent. Despite the positive assessment of DP3, the interviews revealed that user test participants would have preferred multiple response options. This result is inconsistent with the practice-based requirements, as experts reported that they would want two suggestions. This discrepancy could be explained by the fact that suggestions by the implemented CA are too context-independent due to its rule-based architecture.

In terms of HI research, HIS do not only support the augmentation of SEs through CA suggestions but should also enable CA augmentation through the SE (Dellermann et al. 2019b; Dellermann et al. 2019a). This is predominantly realized by implementing feedback functionalities (Abdel-Karim et al. 2020; Kulesza et al. 2015; Lees et al. 2011; Oliveira et al. 2020; Schneider and Handali 2019). With DP2, the SEs are provided with the option to critically reinforce the CA by using a "thumb-down" button. Even though the analysis of the interviews revealed that this feature is important confirming mutual augmentation intentions, the user test showed that the instantiation of DP2 via the feedback button was not distinct nor fully comprehensible. Thus, many hesitated to use the feedback button not knowing its utility or impact on the interaction with either the customer or the CA. Another reason for the minor usage of the feedback button (25 of 209 interactions) could also be the high satisfaction with the suggestions. As ~ 95 % of the suggestions were used or adapted, many participants did not see the need in giving critical feedback. Research also indicates that people are more likely to be polite and rather positive toward a computer (Nass et al. 1994; Nass and Moon 2000). Hence, for further developments, DP2 could be enhanced by, e.g., integrating a "thumb-up" button for positive feedback. Additionally, future research could specifically focus on this learning feature, i.e., how to best augment the CA.

At last, DP5 was implemented to support the CA's role as a team member ensuring a satisfying hybrid collaboration between SE and CA. Following Social Response Theory (Nass and Moon 2000), the CA was instantiated with a human-like appearance equipped with social cues and anthropomorphic attributes. In general, the evaluation reveals a human-like perception of the CA among the SEs. However, this is tightly connected with the successful implementation of DP3 providing the CA with the ability to propose more personalized suggestions. Hence, the employees could personalize the response options toward the customer. As opposed to CA criticism addressing unnatural interactions (Grudin and Jacques 2019) or response limitations (Amershi et al. 2014; Harms et al. 2019), most participants were surprisingly positive about the variety and use of language. Even though they knew that the nature of the CA is artificial, most reasoned in favor of the perceived humanness. For the ones reasoning against perceived humanness, the CA could be improved by an increased usage of empathetic words as well as conversation beginnings and endings. Nevertheless, to specifically facilitate and nurture the team connection of SE and CA, future research could focus on their distinct interactions, e.g., increased personalization. Additionally, to better examine the impact of perceived humanness on the SEs' satisfaction with the CA, future research could conduct experiments including a baseline condition without a virtual identity of the CA.

Besides the promising results of this research, there are a few limitations to consider. First, we assessed the DPs by deploying our prototype in an artificial evaluation setting as the customers were simulated by the research team. This might have also influenced the high response acceptance by the SEs, i.e., technical performance in terms of typing errors or incomprehensible questions was not in the scope of this study. Second, even though we could confirm a successful application of a rule-based CA, we call for further research to examine if an ML-based CA would have achieved better or different results. This also applies to the amount and form of response suggestions. Additionally, future research should implement a prototype in a more naturalistic setting to evaluate, whether the results remain positive, specifically in terms of SE support and enhanced operational performance. Besides performance, service quality is a criterion that should be addressed in future research by evaluating customer satisfaction with the service provided. At last, our design knowledge for employee-facing CAs could be combined with research on CA-SE handovers (Følstad and Skjuve 2019; Poser et al. 2021), i.e., integrating sequential with simultaneous customer request handling.

17.8 Conclusion

Our paper investigates a conversational interface for HIS with an employee-facing CA toward augmentation and hybrid teamwork between CA and SE enabling their simultaneous handling of customer requests in real-time customer conversations. Thereby, we address the real-world challenge of companies to use AI-based CAs in an efficient way in the frontstage of online customer service, considering their current weaknesses as well as strengths. Following a DSR approach, we present prescriptive knowledge about design and action in the form of MRs and higher-order DPs for an employee-facing CA that, invisible to the customer, supports SEs to process customer requests in real-time. Our findings contribute to research and practice. The results have implications for research about employee-facing CAs, as we provide and extend existing design knowledge. In addition, our investigation of an employee-facing CA contributes to research on HI, as we explore a conversational interface for HIS. Our results serve as promising first insights that can be used to design mutual augmentation and learning via natural language interaction. Furthermore, we adopted findings from team research in order to design a human-centered HIS. The inclusion of this research stream can serve as a starting point for future research. The investigation of the use of an employee-facing CA also has implications for online customer service research, as it offers a solution to find a suitable balance between efficiency (automation) and personalization (human-touch) to conduct service encounters. Besides research-related aspects, we also contribute to practice. The presentation of implementable design knowledge enables companies to deploy a CA in their online customer service. Furthermore, the evaluation of the CA indicates advantages of using this CA in combination with SEs. These insights are helpful for companies to decide on the application of an employee-facing CA in order to increase their operational efficiency.

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