Artificial Intelligence and Robots in Services – Theory and Management of (Future) Human–Robot Service Interactions

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Abstract

During the past decade, service robots have increasingly been deployed in a wide variety of services, where they co-produce service outcomes with and for the benefit of internal or external customers within human–robot service interactions (HRSI). Although the introduction of different service robot types into the marketplace promises efficiency gains, it changes premises of service encounter theory and practice fundamentally. Moreover, introducing service robots without considering external or internal customers' needs can lead to negative service outcomes. This thesis aims to generate knowledge on how the introduction of different service robot types (i.e., embodied and digital service robots) in internal and external service encounters changes fundamental premises of service encounter theory and impacts HRSI outcomes. In doing so, it leverages different scientific methods and focuses on external service encounters with digital and embodied service robots, as well as internal service encounters with digital service robots.

Chapter 2 aims to advance service encounter theory in the context of HRSI in external service encounters by conceptually developing a service encounter theory evaluation scheme to assess a theory's fit to explain HRSI-related phenomena. The scheme includes individual and contextual factors that bound theoretical premises and, hence, supports scholars in assessing standing service encounter theories. The chapter also puts forth an exemplary assessment of role theory and provides detailed avenues for future research.

Chapter 3 aims to synthesize the great wealth of knowledge on HRSI related to external service encounters with embodied service robots. By conducting a comprehensive systematic literature review, the chapter identifies 199 empirical research articles across scientific fields that can inform service research on how to successfully introduce service robots into the organizational frontline. To organize the plethora of research findings, this chapter develops a new structuring framework (D^3: design, delegate, deploy). It utilizes this framework to provide a comprehensive overview of the empirical HRSI literature, delineates practical implications, and identifies gaps in literature to identify promising future research avenues.

Chapter 4 also addresses HRSI in external service encounters but focuses specifically on the transformative potential of embodied service robots to enhance vulnerable consumers' (i.e., children and older adults) well-being in social isolation. To identify how different robots can enhance well-being, this chapter follows a conceptual approach and integrates findings from service research, social robotics, social psychology, and medicine. The chapter develops a typology of robotic transformative service (i.e., entertainer, social enabler, mentor, and friend) as a function of consumers' state of social isolation, well-being focus, and robot capabilities and a future research agenda for robotic transformative service research (RTSR). This work guides service consumers and providers, as well as robot developers, in identifying and developing the most appropriate robot type for advancing the well-being of vulnerable consumers in social isolation.

Finally, Chapter 5 focuses on HRSI research in the context of interactions with digital service robots in internal service encounters. Based on a comprehensive literature review paired with a qualitative study, it conceptionally develops a new concept of a collaborative, digital service robot: a collaborative intelligence system (i.e., CI system) that co-produces service with employees. Drawing from service encounter needs theory, the chapter also empirically tests the effect of CI systems on employee need fulfillment (i.e., need for control, cognition, self-efficacy, and justice) and, in turn, on responsibility taking in two scenario-based experiments. The results uncover divergent mechanisms of how the fulfillment of service encounter needs drives the effect of CI systems on outcome responsibility for different employee groups. Service scholars and managers benefit from a blueprint for designing collaborative digital service robots and an understanding of their effects on employee outcomes in service co-production.

In summary, this thesis contributes to literature by providing new insights into different types of HRSI by consolidating HRSI knowledge, developing and advancing HRSI concepts and theory, and empirically investigating HRSI-related phenomena. The new insights put forth in this thesis are discussed and implications for service theory and practice are delineated.

Zusammenfassung

Im letzten Jahrzehnt wurden Serviceroboter zunehmend in einer Vielzahl von Dienstleistungen eingesetzt, wo sie mit und zum Nutzen von internen oder externen Kunden im Rahmen von Mensch-Roboter-Service-Interaktionen (MRSI) Serviceergebnisse co-produzieren. Während die Einführung verschiedener Arten von Servicerobotern auf dem Markt Effizienzgewinne verspricht, verändert sie grundlegende Prämissen der Theorie und Praxis von Dienstleistungsinteraktionen. Darüber hinaus kann

die Einführung von Servicerobotern ohne die Berücksichtigung von Bedürfnissen externer oder interner Kunden zu negativen Serviceergebnissen führen. Ziel dieser Dissertation ist es, Wissen darüber zu generieren, wie die Einführung verschiedener Serviceroboterpypen (d. h. verkörperte und digitale Serviceroboter) in internen und externen Dienstleistungsinteraktionen grundlegende theoretische Prämissen von Dienstleistungsinteraktionen verändert und sich auf die Ergebnisse von MRSI auswirkt. Um dieses Ziel zu erreichen, werden unter Einsatz verschiedener wissenschaftlicher Methoden sowohl externe Dienstleistungsinteraktionen mit digitalen und verkörperten Servicerobotern als auch interne Dienstleistungsinteraktionen mit digitalen Servicerobotern untersucht.

Kapitel 2 zielt darauf ab, die Theorie der Dienstleistungsinteraktion im Kontext von MRSI in externen Dienstleistungsinteraktionen weiterzuentwickeln und konzeptioniert ein Bewertungsschema für bestehende Theorien der Dienstleistungsbegegnung, um die Eignung einer Theorie zur Erklärung von MRSI-bezogenen Phänomenen zu beurteilen. Das Schema umfasst individuelle und kontextuelle Faktoren, die die ursprünglichen theoretischen Prämissen von Mensch-zu-Mensch Dienstleistungsinteraktionen beeinflussen und unterstützt somit Wissenschaftler bei der Bewertung von Theorien zur Verwendung im MRSI Kontext. Das Kapitel enthält außerdem eine beispielhafte Bewertung der Rollentheorie und zeigt detaillierte Wege für zukünftige Forschung auf.

Kapitel 3 zielt darauf ab, die große Fülle an Wissen über MRSI im Kontext externer Dienstleistungsinteraktionen mit verkörperten Servicerobotern zu synthetisieren. Durch eine umfassende systematische, interdisziplinäre Literaturanalyse identifiziert das Kapitel 199 empirische Forschungsartikel, die im Rahmen der Dienstleistungsforschung Erkenntnisse darüber liefern, wie Serviceroboter erfolgreich in den Dienstleistungsprozess eingebunden werden können. Um die Fülle an Forschungsergebnissen zu ordnen, entwickelt dieses Kapitel ein neues, strukturierendes Modell (D^3 framework: design, delegate, deploy). Im Rahmen des Kapitels wird das Modell genutzt, um einen umfassenden Überblick über die bestehende empirische MRSI-Forschung zu geben, praktische Implikationen abzuleiten und Forschungslücken aufzuzeigen.

Kapitel 4 befasst sich ebenfalls mit MRSI in externen Dienstleistungsinteraktionen, konzentriert sich aber auf das transformative Potenzial von verkörperten Servicerobotern zur Steigerung des Wohlbefindens von sozial isolierten, vulnerablen Verbrauchern (d. h. Kinder und ältere Erwachsene). Um herauszufinden, wie verschiedene

Roboter das Wohlbefinden steigern können, folgt das Kapitel einem konzeptionellen Ansatz und integriert Erkenntnisse aus der Dienstleistungsforschung, der sozialen Robotik, der Sozialpsychologie und der Medizin. Dabei wird eine Typologie von vier transformativen Robotern in Abhängigkeit vom Zustand der sozialen Isolation des Verbrauchers, der Art des Wohlbefindens und den Fähigkeiten des Roboters entwickelt. Weiterhin bringt das Kapitel eine detaillierte Forschungsagenda für zukünftige Forschung im Kontext transformativer Dienstleistungserstellung durch Roboter hervor. Diese Arbeit hilft sowohl Dienstleistungsnehmern und -anbietern als auch Roboterentwicklern bei der Identifizierung und Entwicklung des am besten geeigneten Robotertyps zur Förderung des Wohlbefindens von sozial isolierten, vulnerablen Verbrauchern.

Schließlich konzentriert sich Kapitel 5 auf die MRSI-Forschung im Kontext interner Dienstleistungsinteraktionen mit digitalen Servicerobotern. Auf Basis einer umfangreichen Literaturanalyse gepaart mit einer qualitativen Studie wird ein neues Konzept eines kollaborativen, digitalen Serviceroboters entwickelt: ein Collaborative Intelligence System (CI System), das in Zusammenarbeit mit Mitarbeitern Dienstleistungsergebnisse co-produziert. Weiterhin wird anhand zweier szenariobasierter Experimente empirisch untersucht, ob CI Systeme psychosoziale Bedürfnisse von Mitarbeitern befriedigen können und damit die mitarbeiterseitige Übernahme von Verantwortung für gemeinsam produzierte Ergebnisse fördert. Die Ergebnisse decken für verschiedene Mitarbeitergruppen unterschiedliche Mechanismen auf, wie die Erfüllung von Bedürfnissen in der Dienstleistungsinteraktionen die Wirkung von CI Systemen auf die mitarbeiterseitige Übernahme von Verantwortung beeinflusst. Dienstleistungsforscher und -manager profitieren von einer Blaupause für die Gestaltung kollaborativer, digitaler Dienstleistungsroboter und einem Verständnis für deren Auswirkungen auf Mitarbeitende.

Zusammenfassend leistet diese Dissertation einen Beitrag zur Dienstleistungsforschung, indem sie neue Erkenntnisse über verschiedene Arten von MRSI liefert, das bestehende MRSI-Wissen konsolidiert, neue MRSI-Konzepte und -Theorien entwickelt bzw. weiterentwickelt und MRSI-bezogene Phänomene empirisch untersucht. Die neuen Erkenntnisse werden diskutiert und Implikationen für die Dienstleistungstheorie und -praxis abgeleitet.

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List of Abbreviations

ABC	Affect-Behavior-Cognition
ACM DL	Association for Computing Machinery Digital Library
AI	Artificial Intelligence
ANZ	Australia and New Zealand Banking Group
ATM	Automatic Teller Machine
AVE	Average Variance Extracted
ANOVA	Analysis of Variance
CC	Complexity Check
cf.	Confer
CFA	Confirmatory Factor Analysis
CI	Collaborative Intelligence
CI (Section 5.3.5)	Confidence Intervall
COVID-19	Coronavirus Disease 2019
CR	Composite Reliability
D^3	Design, Delegate, Deploy
DBS Bank	Development Bank of Singapore
EFA	Explorative Factor Analysis
e.g.	Exempli gratia
ESCI	Emerging Sources Citation Index
et al.	Et alii
FR	Factor Reliability
HCI	Human-Computer Interaction
HI	Hybrid Intelligence
HRI	Human-Robot Interaction
HRSI	Human-Robot Service Interaction
HTMT ratio	Heterotrait–Monotrait Ratio
i.e.	Id est

IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
ISO	International Organization for Standardization
KPMG	Klynveld, Peat, Marwick, Goerdeler
MANCOVA	Multivariate Analysis of Covariance
MAT	Machines as Teammates
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PwC	PricewaterhouseCoopers GmbH
RC	Realism Check
RQ	Research Question
RTSR	Robotic Transformative Service Research
SAR	Socially Assistive Robots
SCI	Science Citation Index
SCI-E	Science Citation Index Expanded
SD	Standard Deviation
S.E.	Service Encounter
SENT	Service Encounter Needs Theory
SI	Service Interface
SPSS	Statistical Package for the Social Sciences
SSCI	Social Sciences Citation Index
TAM	Technology Acceptance Model
TSR	Transformative Service Research
U.S.	United States
WOS	Web of Science

List of Symbols

b	Coefficient (Indirect Effect)
c'	Path Coefficient (Direct Effect)
c	Coefficient (Total Effect)
df	Degrees of Freedom
f	Female
F	F Statistic
I_r	Intercoder Reliability
m	Male
M	Mean
n	Sample Size
p	Significance Value

1. Introduction

1.1 Relevance and Scope

Artificial intelligence (AI) changes the service game. AI-based technologies enable different service robot types, such as embodied robots, chatbots, or avatars, to learn from previous interactions, adapt their behavior, and interact with their counterpart in a human-like manner (Fong et al., 2003; Kaplan & Haenlein, 2019). Thus, AI-enabled service robots are inherently different from the current, well-established, static service technologies, such as self-service terminals (e.g., ATMs or check-in machines). During the past decade, service robots have increasingly been deployed in a wide variety of services, where they co-produce service outcomes with and for the benefit of internal or external customers within human–robot service interactions (HRSI) (Lu et al., 2020; Wirtz et al., 2018).

For example, in external service encounters, embodied service robots welcome customers to hotels and serve them in restaurants, give additional information about products in stores, or assist the elderly with walking to support their health (Henschel et al., 2021; KPMG, 2016). Digital service robots, such as Apple's Siri or Amazon's Alexa, read cooking recipes at home and support customers in booking tables at restaurants and placing shopping orders (PwC, 2018). Within organizations, service robots support employees' (i.e., internal customers) decision-making processes, data analyses, or task organization. For example, AI-enabled digital service robots are deployed to support physicians in diagnosing diseases (Tseng et al., 2020), HR professionals in screening applications (Marr, 2019), or analysts in deciding on credit loans (DBS Bank, 2021). The total number of service robot sales is expected to increase by 35 % annually over the next decade (Research Nester, 2022), and the integration of service robots has positive efficiency effects on service firms (Wirtz et al., 2018). For instance, AI-enabled service robots can provide individually tailored and efficient service 24/7 (Wirtz et al., 2018).

Moreover, research shows that different service robot types already successfully take on different service roles (e.g., concierge, Shin & Jeong, 2020 or medical assistant, Čaić et al., 2018) and, in a recent study, most customers have described positive experiences with service robots in the hospitality context (Huang et al., 2021). However, the integration of service robots into the marketplace profoundly reshapes service encounters and challenges some of the fundamental premises of traditional service encounter theory (Kaartemo & Helkkula, 2018; Subramony et al., 2018). For instance, more efficient, individual, and around-the-clock available service provision through service robots changes customer expectations (Stock & Merkle, 2018). At the same time, service robots are not yet equipped to take on every service task, and customers do not always prefer service robots over human employees (Rafaeli et al., 2017).

A famous example of failed service robot integration in external service encounters is the case of the Henn-na Hotel in Japan. Originally deploying almost exclusively service robots, the hotel had to fire half of its robotic staff because the robots failed to reduce the cost or workload for employees and repeatedly led to customer complaints, for example, because the robots broke down or could not answer basic questions (Hertzfeld, 2019). Moreover, first service research suggests that humanoid service robots, as compared to human staff, can cause customer compensation behavior and lead to unhealthy food choices in customers (Mende et al., 2019), and replacing human staff with service robots can lead to damages to service firms' reputations because customers might consider such measures unethical and unsocial (McLeay et al., 2021). In the context of internal service encounters, research suggests that when employees are paired with digital service robots in decision-making processes, the employees do not fully trust the system and refuse to use it when it does not work flawlessly right away (Dietvorst et al., 2015). Moreover, research suggests that when employees collaborate with service robots without their employees' needs and work environment being considered, can diminish their meaning of work and sense of responsibility for jointly produced service outcomes (Santoni de Sio & Mecacci, 2021; Zerilli et al., 2019).

Furthermore, if companies decide to implement service robots in their organization, external and internal customers alike lose the opportunity to obtain human service. Matzner et al. (2018) stress that organizations need to consider trade-off challenges when replacing humans with robots in service encounters. Human service has been related to positive customer outcomes, such as customer delight (Collier et al., 2018), and is preferred over technology in some service settings (Rafaeli et al., 2017). It is still unclear whether service robots, when compared with human service providers, can satisfy the relevant functional and psychological needs of external and internal customers in service encounters (Bradley et al., 2010; Wirtz et al., 2018). Even though some service robots such as Google's Duplex already mimic human voices and behavior in a way that they can no longer be recognized as machines (Chen & Metz, 2019), the uncanny valley concept (Mori et al., 2012) suggests that an artificial agent that resembles a human too closely yet not close enough could be perceived as creepy and cold (van Doorn et al., 2017). Thus, to stay competitive, service firms must actively manage the integration of service robots at the frontline and within their organization to leverage the full potential of service robots, avoid negative effects on customers and employees, and prevent service breakdowns (Mende et al., 2019; Wirtz et al., 2018).

Several calls for research to unravel the antecedents, consequences and mechanisms of HRSI, as well as their impact on service theory, have been placed over the past years (Ostrom et al., 2015; Ostrom et al., 2021; Wirtz et al., 2018). Even though there is a great wealth of knowledge on human–robot interaction (HRI) in general that can inform service scholars and managers and service research has already begun to unravel the implications of HRSI for service firms, significant gaps remain (De Keyser & Kunz, 2022). The present thesis contributes to the emerging HRSI research stream by conducting four research projects related to different types of HRSI that have been guided by one central research question:

How does the introduction of different service robot types in external and internal service encounters require alterations of service encounter theory and impact service encounter outcomes?

Next, a typology of HRSI is developed that defines four different types of HRSI. Then, the focus of and the research gaps addressed in this thesis' four individual research projects in relation to the HRSI typology are carved out. Finally, the contributions to literature are delineated, and the structure of the thesis is presented.

1.1.1 Typology of Human–Robot Service Interactions

The term *human–robot service interactions* (HRSI) refers to all interactions between human internal and external customers[1] and service robots in a service setting (Bock et al., 2020; Larivière et al., 2017; Wirtz et al., 2018) and can be classified along two dimensions: (1) service encounter and (2) service robot type.

Service Encounter Type. *External service encounters* are generally defined as distinct moments in which customers interact with a concrete service interface (Solo-

[1] Although the terms customer and consumer are often used interchangeably, there is a subtle difference in their meaning. Customers are people who buy goods or services and, hence, pay for the goods or services they select. Consumers use goods or services but do not necessarily select and pay for them. For example, when parents buy toys for their child, the parents are the customers and the child is the consumer (Burns, 2019). In this thesis, Chapters 3 and 4 refer to consumers because the scope includes interactions with elderly, children, and patients with limited agency who usually do not buy the robotic services themselves. The other chapters refer to customers because the term is more commonly used in the services field and includes the notion of internal customers (Gremler et al., 1994).

mon et al., 1985). Service encounters are social interactions that fulfill individual functional and psychosocial needs alike (Bradley et al., 2010; Chung-Herrera, 2007; Wilder et al., 2014). For example, when customers meet their bank advisors for an investment consultation, their functional need is to find a financial product to invest their money in a way that best fits their personal investment goals while considering their risk preferences. At the same time, the service interaction with their personal advisor fulfills, inter alia, the psychosocial need for belongingness and social contact (Bradley et al., 2010).

Traditionally, these interactions would occur between human employees representing the service firm and human customers (Solomon et al., 1985). For successful service interactions, both parties must integrate resources and, thus, co-produce service outcomes together (Bendapudi & Leone, 2003; Vargo & Lusch, 2007). To stay with the example of financial services, employees systematically ask customers about their financial situation and investment goals to determine which product might fit the customer best and explain the various options customers have. For an optimal service outcome and, thus, the best-fitting financial product, customers must provide the required information and request additional information in case of ambiguity or difficulty understanding the differences between financial products. Hence, the outcome depends on an appropriate exchange of relevant information between both parties.

With the advancement of AI technologies and robotic engineering, service interfaces are evolving and becoming increasingly technology dominant, including, for example, digital service robots acting as service interfaces (Larivière et al., 2017) that co-produce service outcomes with customers. Based on this notion, Larivére et al. (2017) coin the term service encounter 2.0, which reflects the current service reality better and is defined as “any customer-company interaction that results from a service system that is comprised of interrelated technologies (either company or customer-owned), human actors (employee and customers), physical/digital environments and company/customer processes” (p. 239). This overarching definition represents a variety of encounters, from simple dyadic interactions to complex interactions with multiple entities enabled by service ecosystems. It entails human-to-human, human-to-technology, and technology-to-technology interactions (De Keyser et al. 2019). The present thesis focuses on dyadic, human-to-technology service encounters. Common examples of this service encounter type would be customers interacting with a chatbot or embodied service robot to get information about a service (e.g., flight or shop locations in malls; Lufthansagroup, 2019, Sabelli & Kanda, 2016).

Although Larivière et al.'s (2017) definition is universal, it lacks the perspective of services delivered within organizations. Service interactions that occur in an organizational context where internal customers are the employees of an organization are called *internal service encounters* (Gremler et al., 1994). Just like in external service encounters, the interfaces of service providers that co-produce service outcomes with employees within organizations can vary from human actors to various types of service robots (Bock et al., 2020). For example, when new software is installed, employees might be assisted by a human computer technician from the internal information systems department who explains how to operate the new system (Gremler et al., 1994). Today, internal services are increasingly delegated to AI-enabled service robots (Bock et al., 2020). For example, the company BetterHR (2022) provides chatbots that take over onboarding tasks and guide new employees through the onboarding process, answering common questions, and collaboratively filling in the necessary legal forms. Hence, the employee and the service robot collaboratively create an outcome that serves the employees' organization. While collaborating, just like external customers, internal customers seek to satisfy their functional and psychosocial needs (Bradley et al., 2010; Gremler et al., 1994). However, the needs of internal customers differ from those of external customers because they are directly related to carrying out the employee's job responsibilities and are related to the company rather than the employees' personal goals (Bradley et al., 2010; Gremler et al., 1994). Moreover, internal customers differ from external customers in that they have no choice in terms of alternative service suppliers and, thus, are stuck with their internal service provider (Gremler et al., 1994).

This thesis takes a particular interest in understanding how dyadic, human-to-technology service encounters impact human actors in internal and external service encounters.

Service Robot Type. According to the International Organization for Standardization (ISO; 2013), service robots are generally defined as "robots that perform useful tasks for humans or equipment excluding industrial automation applications (e.g., manufacturing, assembly)". The ISO Technology Committee also notes that, although robots used in production that are interactive and articulate are defined as industrial robots, robots with similar abilities that provide services (e.g., delivering food) are service robots. Hence, service robots need to be able to actively interact with their human counterparts, which is mostly achieved through technology based on AI

(Kaplan & Haenlein, 2019). AI systems are defined as systems that are “able to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptations” (Kaplan & Haenlein, 2019, p. 17). Hence, these systems can adapt autonomously to different situations based on big data analyses.

Based on this understanding of AI systems, service research refines the general ISO definition and defines service robots as “system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to an organization’s customers” (Wirtz et al., 2018, p. 909). Although Wirtz et al.’s (2018) well-established definition focuses on external customers of organizations that interact with various types of service robots, AI-enabled service robots can also be implemented to provide services within organizations (Bock et al., 2020). Hence, for the present thesis, the original definition of Wirtz et al. (2018) is extended with the notion of internal service encounter and adapted as follows: *service robots are system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to an organization’s external or internal customers*.

As per this definition, service robots can come in various manifestations (Wirtz et al., 2018) and with different levels of social interaction abilities (Breazeal, 2004). They can be *digital* and, hence, presented only digitally (e.g., chatbots, avatars, interactive support software) or *embodied* and, thus, have a physical representation (e.g., social robots such as Pepper or NAO; Wirtz et al., 2018). Digital and embodied service robots can be designed as mechanical, humanoid, or anthropomorphic, thus having almost no human-like features (e.g., Baxter), design features that are inspired by humans (e.g., NAO), or their design fully resembles a human (e.g., Sophia; Wirtz et al. 2018). These design choices can directly or indirectly impact a service robot’s ability to exhibit nonverbal and verbal cues to express emotions and intentions in a human-like manner (Breazeal, 2004), which, in turn, determines if they are perceived as peers and interaction partners (Fong et al., 2003) in service interactions[2].

While digital service robots are limited to digitally represented features that enable them to display social behavior in service interactions, embodied service robots’ physical bodies can be designed to have certain haptic properties, such as soft,

[2] In the robotics literature, robots that can exhibit nonverbal and verbal cues to express emotions and intentions in a human-like manner (Breazel, 2004) and are perceived as peers (Fong et al., 2003) are referred to as social robots. For the present thesis, it is assumed that service robots have the abilities of social robots to interact with external and internal customers but are still referred to as service robots if not otherwise specified in the individual chapters of this thesis.

human-like skin, which can impact service outcomes (Yamashita et al., 2019). Another distinction between digital and embodied service robots is that the functionality of the latter to display social behavior greatly depends on their degrees of freedom, which determines their dexterity (Čaić et al., 2019). The more dexterity service robots have, the smoother they can move and physically interact with their counterparts. For example, dexterity is important when service robots in elderly care carry trays of water without spilling.

Based on the different types of service encounters and service robots, four HRSI types can be defined, which are depicted in Figure 1: interactions of (1) customers and embodied service robots or (2) digital service robots in external service encounters and interactions of (3) employees and embodied service robots or (4) digital service robots in internal service encounters.

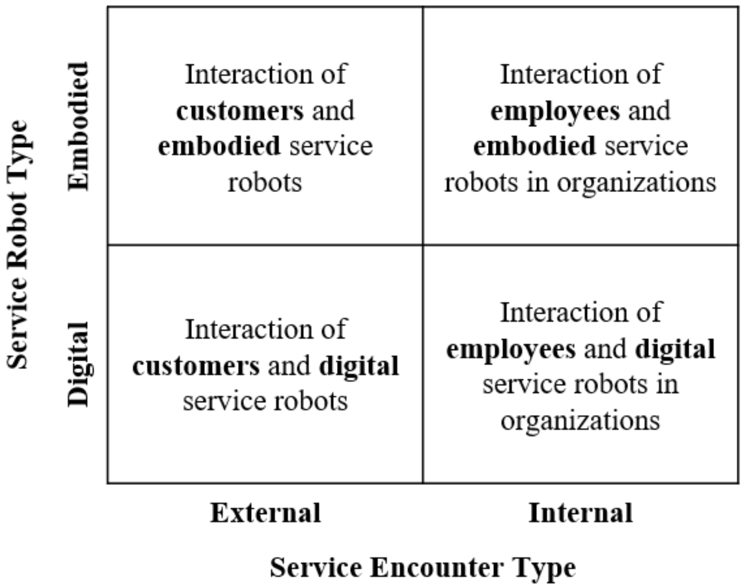


Figure 1: Typology of Human–Robot Service Interactions

1.1.2 Focus of this Thesis in Relation to the HRSI Typology

The present thesis aims to generate knowledge on how the introduction of different service robot types in internal and external service encounters changes fundamental premises of service encounter theory and impacts HRSI outcomes. While all quadrants of the HRSI typology have potential for further research, the current thesis focuses on external service encounters with digital and embodied service robots, as well as internal service encounters with digital service robots, for two main reasons.

First, this thesis focuses on external service encounters with digital and embodied service robots because these encounters are of high practical relevance and have already sparked a lot of interdisciplinary research (De Keyser & Kunz, 2022; Wirtz et al., 2018). Most robots are designed for service interactions with external customers (KPMG, 2016), and sales for customer-facing service robots are projected to grow on average by 35 % annually between 2022 and 2030 (Research Nester, 2022). With the improvement of AI and robotics technology combined with a workforce crisis in Europe and the United States (Weber, 2021), there will be an increasing number of application opportunities for different types of service robots in customer-facing roles. To equip service researchers interested in studying such HRSI-related phenomena with sound theoretical bases, it is crucial to assess standing theoretical bases (De Keyser & Kunz, 2022). Moreover, Lim et al. (2022) point out that the emergence of a new, interdisciplinary research stream such as HRSI calls for a consolidation of extant, related knowledge and conceptual work as a way to give scholars a structured overview of existing knowledge, provide new conceptual frameworks, and point out relevant gaps.

Second, the current thesis focuses on internal service interactions with digital robots. Even though digital service robots are increasingly introduced to co-produce service with employees (Mädche et al., 2019), empirical research on HRSI in internal service encounters with a focus on the employee perspective when collaborating with service robots is scarce (De Keyser & Kunz, 2022). This void calls for a focus on empirical investigations of interactions between employees and service robots within organizations to move the HRSI field forward.

The focus of each of the present thesis' chapters is depicted in Figure 2.

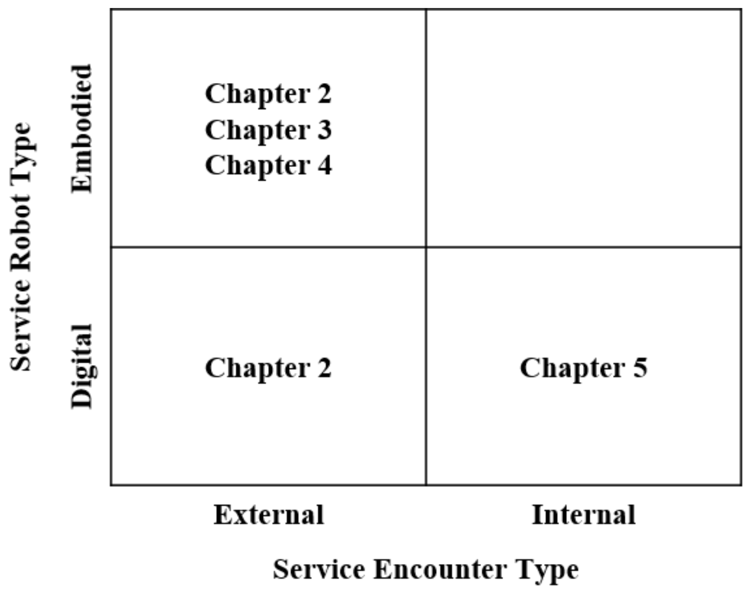


Figure 2: Focus of this Thesis

Chapter 2 focuses on service encounter theory evaluation and applies to external service encounters between customers and both service robot types. Hanelt et al. (2021) stress that the emergence of new phenomena resulting from the digital transformation change empirical reality which challenges the fit of established theoretical models. Hence, there is a need to assess theories regarding how they can be applied to a new context, how their premises change, and how they might need to be altered to fit in a changed context. In the service literature, Bock et al. (2020) emphasize that the introduction of digital technologies, such as AI and different service robot types that augment or substitute human service providers (i.e., service encounter 2.0), might require modifications to existing theories because the integration of service robots fundamentally alters customer interaction behavior and affects customer experiences (Bock et al., 2020; Larivière et al., 2017; Verhoef et al., 2021). As a result, calls for service encounter theory adaptation or development in the context of service robots have been repeatedly echoed (De Keyser & Kunz, 2022; Novak & Hoffman, 2019; Ostrom et al., 2021; Schepers & van der Borgh, 2020; van Doorn et al., 2017).

Extant research has started to fill this gap by adapting standing service encounter theories (i.e., service encounter 1.0 theories) to the HRSI context or assessing service robots' current and future impact on prominent service encounter theories. For example, both Wirtz et al. (2018) and Stock and Merkle (2017) adapt the technology acceptance model and advance different service robot acceptance models; Blaurock et al. (2022) advance new premises for traditional role theory and develop an integrative framework of robotic role theory. Meanwhile, Bock et al. (2020) review dominant service theories, investigating their relevance in relation to AI-infused service encounters, along with their definition of "service-AI". In doing so, they explore nine relevant service encounter theories in detail and find that most of them have deficiencies when aiming to explain AI-related phenomena and identify a plethora of future research avenues for each theory.

Although all of these works have advanced service encounter theory in the context of HRSI in external service encounters, they fall short of investigating in detail the underlying changes in the evolution of the service encounter from human-to-human to human-to-technology that, in turn, change fundamental premises of service encounter theory and translate them into a more universal assessment scheme for standing service encounter theories. Chapter 2 of this thesis attempts to fill this gap by answering the following research questions:

RQ1: What are the focal changes from human-to-human service encounter 1.0 to AI-based service encounter 2.0?

RQ2: What are the most relevant service encounter 1.0 theories?

RQ3: How do premises in the most relevant service encounter 1.0 theories have to be adapted in the service encounter 2.0 environment to serve as valid theoretical explanations for the processes and outcomes of AI-based service encounter 2.0?

In not limiting the applicability of the advanced service encounter theory evaluation scheme, Chapter 2 includes both digital and embodied service robots in its analyses. To provide detailed insights into successful service robot integration into the organizational frontline, Chapters 3 and 4 take a narrower view and focus on embodied service robots. Although all types of service robots change service encounters, embodied robots engaging in social interactions with customers are expected to ignite the most dramatic transformation of the customer service landscape in the age of service robots (Mende et al., 2019). That is, for example, because embodied service robots (especially when designed humanoid) can engage with customers more meaningfully on a social level than digital robots and evoke a greater social presence (Mende et al., 2019; van Doorn et al., 2017).

As mentioned above, HRSI marks a relatively new research stream in the service literature, and service research is beginning to unravel the implications for customer–firm interactions. However, human–robot interaction is not a ground zero. Other fields, such as human–computer interaction (HCI), information systems, and psychology have amassed a wealth of empirical findings that can inform service research and provide a head-start in successfully designing service interactions of customers and service robots in external service encounters. This plethora of existing knowledge on HRSI from different fields calls for a systematic consolidation. Synthesizing and structuring extant knowledge, as well as identifying relevant gaps in literature, is crucial to inhibit redundant research and pave the way for new research projects (Lim et al., 2022).

Growing applications for service robots have already spawned surging interest to consolidate the extant HRSI literature in service research. Some of the first reviews highlight the application of robots in service contexts, with a focus on the antecedents and outcomes for customer service (Xiao & Kumar, 2021), value co-creation (Kaartemo & Helkkula, 2018), the impact on employees and customers (Lu et al., 2020), classifications of robot communication behaviors (van Pinxteren et al., 2020), or understanding the effect of anthropomorphism in robotic service provision (Blut et al., 2021). De Keyser and Kunz (2022) take a more overarching view by mapping the literature on HRSI in general by examining theories, context, study characteristics, and methodology.

Although all of these reviews provide valuable insights into the HRSI literature about external service encounters with either digital or embodied or partly both service robot types, they mostly base their implications on a limited set of empirical findings on HRI in service at that time or have restricted foci. For example, Kaartemo and Helkkula (2018) and Lu et al. (2020) mainly derive their insights from conceptual articles published in business and services marketing outlets, so they are limited by the nascent stage of empirical HRI research in these fields at the time. Although De Keyser and Kunz identify a great amount of empirical work in the service and business literature in 2022, they do not put forth a structuring framework and neglect insights of HRSI studies from other scientific disciplines. Moreover, while van Pinxteren et al. (2020) and Blut et al. (2021) provide multidisciplinary reviews, their scope is restricted purely to communication- or anthropomorphism-related studies. Hence, all of these reviews offer very valuable insights for the respective research questions they advance; however, none of them provides a structured synthesis of the empirical insights on HRSI with embodied service robots in external service encounters across scientific fields.

Thus, the aim of Chapter 3 is to provide an integrated and structured overview of extant knowledge on customer interactions with embodied service robots in external service encounters. Moreover, based on this review Chapter 3 aims to delineate implications for service researchers and managers on how to successfully introduce embodied service robots into the organizational frontline and what research gaps remain.

RQ4: What overarching guiding structure organizes the extant HRSI literature?
RQ5: What is the status quo of empirical insights on HRSI across scientific fields, and how can these insights be synthesized to inform researchers and practitioners on the successful integration of embodied social robots in customer-facing services?
RQ6: What future research avenues emerge from an integrative perspective on HRSI?

The global COVID-19 pandemic and its condemnation measures have had a profound impact on service interactions in general and fostered the adoption of service robots (Finsterwalder & Kuppelwieser, 2020). Worldwide lockdown measures included social isolation, and service firms needed to quickly update their customer touchpoints (Finsterwalder & Kuppelwieser, 2020). For example, elderly care homes employed service robots to serve food to residents (Getson & Neja, 2021). At the same time, research shows that social isolation has immediate and long-term detrimental psychological health consequences for consumers (Brooks et al., 2020). These negative effects are exacerbated for vulnerable consumer groups, particularly older adults and children (Holmes et al., 2020).

Service research has put forth manifold conceptual and empirical evidence of how service can transform the well-being of consumers (Anderson, 2010; Anderson et al., 2013; Anderson & Ostrom, 2015; Gustafsson et al., 2015) and increasingly accentuates the different roles of embodied service robots in service provision (Čaić et al., 2018; Mende et al., 2019; Schepers & Streukens, 2022). Although research has shown that service robots generally have the potential to increase vulnerable consumers' well-being (Moerman et al., 2019), a systematic integration of HRSI with embodied service robots in external service encounters and transformative service research (TSR) is still in a nascent stage. Sparked by the tolls that social isolation measures take on vulnerable consumers, Chapter 4 of this thesis addresses this gap, examining in detail how embodied service robots can enhance the psychological well-being of children and older adults in external service encounters during social isolation by answering the following research question:

> *RQ7: How can social service robots assist vulnerable consumers to attenuate, or even reverse, the negative psychological health consequences of social isolation and advance well-being?*

Finally, Chapter 5 of this thesis aims to advance knowledge of HRSI in the context of internal service encounters with digital service robots. Research on employees as internal customers who interact with service robots is scarce, and research calls for the integration of the employee perspective in relation to technology-infused service encounters (Larivière et al., 2017; Ostrom et al., 2021). Although the literature on employee perspectives when working with embodied robotic colleagues is emerging (Paluch et al., 2022; Willems et al., 2022), digital service robots are implemented more often in internal contexts to co-produce services with employees, and applications such as digital assistants for employees in professional services are manifold (Mädche et al., 2019). Following this trend, the current thesis focuses on advancing knowledge about interactions between digital service robots and employees while acknowledging the potential for future research that investigates interactions between employees and embodied service robots.

Most research that focuses on how collaborations with digital service robots and employees unfold was put forth in the information systems literature (e.g., Dellermann et al., 2019; Seeber et al., 2020). This research field has also first coined digital service robots that can collaborate on a joint task with an employee as collaborative intelligence (CI) systems (Epstein, 2015). Even though employee–CI system interactions describe an act of internal service co-production between service robots and employees, they have rarely been analyzed through a service lens (Ostrom et al. 2021).

Research suggests that collaborations between CI systems and employees bring efficiency advantages for service firms (Davenport et al., 2020; Marinova et al., 2017), however, they can have negative effects as well such as diminished employee responsibility taking (Santoni de Sio & Mecacci, 2021). To address this issue, the present research aims to shed light on what CI system features foster employee responsibility taking and how this effect can be explained. In doing so, this thesis attempts to answer the following research questions in relation to HRSI with digital service robots in internal service encounters:

RQ8: What are the features that characterize AI systems as CI systems?

RQ9: How does working with CI systems relate to responsibility taking of employees?

1.1.3 Contributions to Research

By answering the research questions, this thesis advances the HRSI literature in several ways along three overarching contributions: (1) knowledge consolidation, (2) theory or concept development, and (3) empirical concept evaluation.

First, Chapters 3, 4, and 5 contribute to service literature by consolidating existing HRSI knowledge related to an external service encounter with embodied robots (Chapters 3 and 4) and internal service encounters with digital robots (Chapter 5). Consolidating the literature related to an emerging, interdisciplinary research field helps researchers and practitioners gain a rapid overview of the current knowledge while supporting scholars in positioning their research and avoiding duplicate efforts (Lim et al., 2022). By conducting a comprehensive, transdisciplinary systematic literature review screening over 13,500 research articles, Chapter 3 identifies 199 empirical research articles that can inform service researchers and managers about the successful integration of embodied service robots in external service encounters. The results provide service scholars and managers with a comprehensive, general overview of the extant, transdisciplinary empirical HRSI literature along several dimensions (e.g., study characteristics, robot type, focal variables, and key insights). Furthermore, Chapter 4 identifies well-being-relevant studies on robot interactions for two vulnerable consumer groups that are affected the most by social isolation because of the COVID-19 pandemic (i.e., children and older adults). In doing so, it provides a comprehensive overview of what is known about embodied service robots' transformative potential, barriers to exploiting this potential, and the effects interactions with embodied social robots have on consumers' eudaimonic well-being. Finally, by systematically conceptualizing the construct of CI systems, Chapter 5 provides an overview of the extant literature on employee–AI collaboration (i.e., service co-production in internal service encounters) and concepts related to CI systems (e.g., hybrid intelligence; Dellermann et al., 2019).

Second, theory assessment and conceptual advancements are crucial to knowledge development (Zaltman, 1983). Theory revisions avoid knowledge saturation, and conceptual work provides new ideas and justifies empirical studies by integrating knowledge and validating what is known (Yadav, 2010; Zaltman, 1983). Such efforts are especially crucial to move emerging fields, such as HRSI, forward (Bock et al., 2020; De Keyser & Kunz, 2022). Chapters 2–5 of this thesis all contribute to literature through HRSI theory or concept development. First, Chapter 2 develops a novel theory evaluation scheme that supports researchers in adapting existing theories to explain phenomena within service encounters between customers and embodied and/or digital service robots. Additionally, the evaluation schema is exemplarily used with role theory, showing researchers which role theory premises need to be adapted when employing role theory for HRSI research. Second, Chapter 3 synthesizes extant knowledge on customer interactions with embodied service robots across scientific disciplines along a newly developed structuring framework (i.e., D^3 framework: design, delegate, and deploy) and derives detailed practical implications for successful customer service robot interaction and points out existing gaps in literature. Third, by integrating knowledge from service research, social robotics, social psychology, and medicine, Chapter 4 develops a typology of four embodied service robots equipped to advance vulnerable consumers' well-being, depending on the state of social isolation (i.e., objective or subjective) and well-being focus (i.e., hedonic or eudaimonic). It also advances an integrative framework of robotic transformative service including boundary factors and provides detailed avenues for future research. Fourth, Chapter 5 systematically delineates the concept of CI systems from extant research in different scientific fields and shows how the new concept relates to other concepts around it. The CI system concept provides clear design features of digital, collaborative service robots that are relevant for service co-production in internal service encounters, hence allowing scholars to study interactions of employees and digital service robots through a service co-production perspective.

Third, Chapter 5 empirically investigates service co-production of employees and digital, collaborative service robots (i.e., CI systems) in internal service encounters by conducting three empirical studies: a qualitative and two experimental studies with different employee groups. The qualitative study further develops and validates the CI systems concept by considering practitioners' perspectives. The results of the experimental studies show that CI systems with pronounced collaborative features fulfill different psychosocial needs for employees. Moreover, the results show that the fulfillment of the need for control and justice mediates the positive effect of CI systems on employee responsibility taking and that this effect differs between employee groups. With the studies in Chapter 5, the present thesis responds to calls for empirical studies on employee interactions with service robots and contributes to existing knowledge on the antecedents, mechanisms, and outcomes of successful employee–service robot collaboration (De Keyser & Kunz, 2022; Ostrom et al., 2021).

1.2 Structure of this Thesis

The current thesis includes seven chapters to answer the underlying research questions, all of which relate to different quadrants of the HRSI typology introduced in Chapter 1 and is organized as follows:

The first chapter provides a general introduction to the thesis topic by clarifying its relevance and scope, deriving the focal research questions, and highlighting the contributions this work makes to research.

Next, Chapter 2 focuses on service encounter theory related to external service encounters with both digital and embodied service robots and critically analyzes the boundary conditions for service encounter 1.0 theories in an HRSI context. The chapter first introduces the boundary conditions of theories before then identifying the most frequently used service encounter 1.0 theories based on a systematic literature review.

Finally, this chapter develops an evaluation scheme to assess standing service encounter theories with respect to their explanatory relevance in the HRSI context. Along this newly developed evaluation scheme, an exemplary evaluation of the most frequently used theory, role theory, is undertaken, and future research needs are identified.

Chapters 3 and 4 focus on external service encounters with embodied service robots. Chapter 3 contains a comprehensive, transdisciplinary, and systematic literature review on consumer interactions with embodied social robots and analyzes a total of 199 empirical research articles. It develops a structuring framework (i.e., D^3 framework) of the dispersed HRSI literature on several dimensions (e.g., method, robot type) and provides detailed practical implications for each framework theme. This review also provides comprehensive directions for future research.

Zooming in, Chapter 4 assesses the transformative potential of embodied service robots to enhance vulnerable consumers' well-being when socially isolated. The chapter conceptually develops a typology of four distinct types of social robots that may foster vulnerable consumers' hedonic and eudaimonic well-being. It also provides a comprehensive overview of extant knowledge related to social robot interactions with vulnerable consumers, as visualized in an integrative framework, and derives detailed avenues for future research.

Chapter 5 presents a conceptualization and empirical study focusing on digital service robots in internal service encounters. Through a thorough literature review paired with a qualitative study, Chapter 5 systematically develops the concept of CI systems for service co-production. Moreover, it includes the results of two scenario-based experiments that test the effect of CI systems on employee need fulfillment and responsibility taking in a banking context. The chapter concludes with a detailed discussion of the results and directions for future research.

Finally, Chapter 6 contains a general discussion of this thesis, outlining managerial and theoretical implications and suggesting future research directions inter alia based on the present thesis' limitations. Chapter 7 provides closing remarks.

2. Service Encounter 1.0 Theories Revisited: Development of an Evaluation Scheme to Assess their Explanatory Relevance in the Service Encounter 2.0 Environment[3]

Abstract

The introduction of service robots changes fundamental premises of service encounter theory which calls for a reassessment of standing theories. The purpose of this paper is to evaluate the explanatory relevance of service encounter 1.0 theories in the service encounter 2.0 environment. To this end, first the focal changes from service encounter 1.0 to 2.0 are outlined and the most relevant service encounter 1.0 theories identified. Second, an evaluation scheme consisting of contextual and individual bounding factors of theoretical assumptions is conceptually developed. Third, the evaluation scheme is exemplarily deployed evaluating role theory. Scholars may leverage the developed evaluation scheme to standing service encounter theories when planning research in the context of human-robot service interaction.

Keywords:

Service Encounter Theories, Evaluation Scheme, Systematic Literature Review, Role Theory

Name of Author:

Marah Blaurock

[3] **Current Status of the Paper:**

A similar version of the paper is published as: Blaurock, M. (2020). Service Encounter 1.0 Theories Revisited – Development of an Evaluation Scheme to Assess Their Explanatory Relevance in the Service Encounter 2.0 Environment, in M. Bruhn & K. Hadwich (Eds.), *Automatisierung und Personalisierung von Dienstleistungen: Konzepte - Kundeninteraktionen – Geschäftsmodelle* (pp. 199-225), Springer Gabler. https://link.springer.com/chapter/10.1007/978-3-658-30166-8_8. Springer Gabler permits including the article of Chapter 2 in the print version of this thesis. The formatting of this paper has been adjusted to fit the formatting of the other sections.

2.1 Introduction

Theories rely on premises, which are statements that are assumed to be true and that one purports to draw conclusions from (Audi, 1999). These premises are bounded by the theorist's values and perceptions of space and time at the time of their development (Bacharach, 1989). Thus, theories must be continually revisited and their assumptions must be evaluated for their explanatory relevance in changed environments.

Service interactions are undergoing a paradigm change as artificial intelligence (AI) and service robots are increasingly being adopted in customer-firm interactions (Teixeira et al., 2017; van Doorn et al., 2017). For instance, many companies already use chatbots or digital agents for customer service (e.g., Jamie, ANZ bank's digital customer support agent), customers search for information and order through digital assistants such as Apple's Siri or Amazon's Alexa, and the Henn-na Hotel in Japan is solely staffed by humanoid service robots. These technological advancements change the nature of the service encounter and the contexts in which services are delivered (Ostrom et al., 2015). For example, they lead to several new actor combinations in service encounters, such as employee-to-technology-to-customer (mediation), customer-to-technology (employee substitution), or even technology-to-technology (customer and employee substitution; De Keyser et al., 2019; Wünderlich et al., 2013).

In recent publications, service scholars systematically outline research directions for academics operating in this new environment (e.g., De Keyser et al., 2019; Matzner et al., 2018; Wirtz et al., 2018) stressing the need for a revision (Novak & Hoffman, 2019; van Doorn et al., 2017) or even for the development (Kunz et al., 2019) of service encounter theories. Scholars have already begun to investigate new encounter types in experimental settings (e.g., Stock & Merkle, 2018) that focus on the question of what is and where is it happening in these interactions. Nevertheless, the questions of *how*, *when*, and *why* and therefore, the explanation and prediction of certain phenomena in service encounters through theory have been neglected. For instance, while (Solomon et al., 1985) relied on role theory, this foundation likely no longer sufficiently serves as a theoretical basis for service encounters 2.0 anymore, since fundamental premises have changed. To illustrate, it is crucial that the service employee, as a role player, has the ability to show emotions in a way that can be detected by their counterpart to evoke emotional contaigion. In interactions with service robots, this premise is not a given.

This paper responds to the calls for service theory revisons and begins to fill this gap by developing an evaluation scheme to evaluate relevant service encounter 1.0 theories on their fit within the service encounter 2.0 environment. This study's first objective is to analyze the focal changes from service encounter 1.0 to service encounter 2.0. The second aim is to identify the most relevant service encounter 1.0 theories. The third objective is to analyze the fit of the most relevant service encounter 1.0 theory in the service encounter 2.0 environment, specifically for an interaction between a human customer and a humanoid socially interactive service robot. To this end, an evaluation scheme is developed. The fourth objective is to derive directions for future research from the insights of this analysis. Thus, this study contributes to the literature by giving scholars an overview over the most relevant service encounter theories and the key developments leading to the service encounter 2.0. It also develops an evaluation scheme for service encounter 1.0 theories, identifying key parameters which challenge their underlying theoretical assumptions. The identified focal factors enable researchers to develop new and to adapt existing models on service interactions, thereby contributing to theory development.

The remainder of this paper is organized as follows. In Section 2.2, I provide background information on theoretical boundary conditions and the evolution from service encounter 1.0 to 2.0. In Section 2.3, I identify and present the most relevant service encounter 1.0 theories in service research, develop the evaluation scheme, and carry out an exemplary evaluation of the identified most relevant service encounter theory. Finally, I discuss the findings and derive opportunities for future research.

2.2 Background

2.2.1 Theoretical Boundary Conditions

Theories seek to reduce complexity as well as to predict and explain natural events. Theoretical statements help to organize and to clearly communicate natural phenomena (Hall & Lindzey 1975 cited by Bacharach, 1989). However, a theory is a statement of relations among concepts within a set of boundary assumptions and constraints. These assumptions encompass the "implicit values of the theorist and the often "explicit restrictions regarding space and *time*" (Bacharach, 1989, p. 498). Further, (Jaccard & Jacoby, 2020) claim that a theory is a social construction. Hence, the theorist's social schemas and beliefs about human behaviors in a service interaction at the time of the theory development bound a theory's scope to the theorist's previous experiences. Moreover, the constructs embedded in theory are the boundary-spanners between the theory and their representation in empirical research (Bacharach, 1989). Thus, the underlying premises and constructs must be measurable in the real world for a theory to be utilizable by researchers.

A theory is deemed useful if it can explain and predict natural phenomena (Bacharach, 1989) . It can then be utilized by researchers in empirical studies to explain and predict effects between variables and/or their outcomes. Therefore, service encounter theories must address *what* will happen (predict), but importantly also *why*, *when*, and *how* (explain). As a consequence, the utility of a theory is directly related to its spatial and temporal restrictions.

Concerning space, if theories can only be utilized in specific environments (e.g., in certain service encounter types), they succumb spatial boundaries. For instance, a theory may only hold in a retail store in which face-to-face encounters take place. Further, if a theory is only applicable in a specific historical time period, it is bounded to the dominant environmental conditions of that time. For instance, as will be outlined in the next section, technology has made a major impact on service delivery. The service encounters that are now possible were unimaginable by most theorists in the past. Thus, theories' temporal boundary conditions must be evaluated; these restrict service encounter theories' utility, falsifiability, and – ultimately – empirical generalizability (Bacharach, 1989; Weber, 2012).

However, with the notion of boundary conditions, a paradox emerges concerning the evaluation of theories by their utility, generalizability, and falsifiability. On the one hand, theories cannot be overly bounded to a certain spatial or temporal condition (e.g., one firm), since they then are not generalizable enough to build a body of research on. On the other hand, overly broad theories that claim to explain almost anything in fact no longer explain anything anymore and cannot be falsified. To be falsifiable, scholars must seek to construct theories that are coherent enough to be refuted yet broad enough to predict and explain specific phenomena (Bacharach, 1989). A solution to this is to evaluate the premises of standing theories to make scholars aware of their boundary conditions. These theories can then be adapted and utilized again for the prediction and explanation of phenomena that until then were bounded by their underlying theoretical assumptions.

2.2.2 Evolution from Service Encounter 1.0 to 2.0

In general, service encounters entail any customer-firm interactions that relate to a core service offering. They describe moments of truth that significantly shape a customer's impression of a service firm (Voorhees et al., 2017). Service interactions encompass pre-core encounters (e.g., calling a restaurant to reserve a table) and post-core encounters (e.g., e-mailing the restaurant about a forgotten jacket) as well as encounters that form part of the core service delivery (e.g., being seated and served at a restaurant). Thus, the core service is defined as the timeframe during which the primary service is delivered. The primary service relates to the customer's initial motivation to use the services offered by the service firm (Voorhees et al., 2017). Owing to the introduction of technologies into service encounters, service delivery is changing fundamentally (Bitner, 2001).

The service encounter 1.0 is defined as "the dyadic (role-driven) interaction of a customer and a service provider" (Surprenant & Solomon, 1987), and thus as the moment of interaction between a customer and a service firm. These interactions may take place face-to-face in physical service settings, over the phone, or online via the Internet through live chat (Bitner et al., 2000). At its core, the service encounter 1.0 is enabled by two human actors: a service employee and a customer. This dyadic nature of the service encounter 1.0 is further underpinned by Czepiel (1990), who insists that research must achieve a bidirectional understanding of human service encounters. While technology may play a mediating role (e.g., phone inquiries), the customer's counterpart in service encounters 1.0 is always a human service provider.

The service encounter 2.0 has been defined as "any customer-company interaction that results from a service system that is comprised of interrelated technologies (either company or customer owned), human actors (employee and customers), physical/digital environments and company/customer processes" (Larivière et al., 2017, p. 239). It entails interactions that are not necessarily between two humans and is enabled by complex service systems. For instance, Larivière et al.'s (2017) definition encompasses interactions between a customer and a service firm via an autonomous technological device owned by a customer. Thus, it describes a quantum leap from the previous, restricted definition of the service encounter 1.0 and enables several new technology-infused service encounters (De Keyser et al., 2019) in various environments with different service interfaces (Wirtz et al., 2018).

Traditionally, service researchers focused on studying service encounters between human customers and frontline employees – service interactions 1.0. However, at the start of the 21st century, several scholars began to stress the importance of technology infusion in frontline service interactions (Bitner, 2001). Thereby, frontline service technology is defined as “any combination of hardware, software, information and/or networks that supports the co-creation of value between a service provider and customer at the organizational frontline” (De Keyser et al., 2019, p. 158). Accordingly, service scholars began to study phenomena in this new environment. For instance, service researchers have studied the impacts of technologies such as self-service terminals (Blut et al., 2016; Meuter et al., 2000), smart interactive services (Wünderlich et al., 2013), and – recently – chatbots (Araujo, 2018; Riikkinen et al., 2018) as well as embodied service robots (Čaić et al., 2018; Stock & Merkle, 2018) on various customer and firm outcomes.

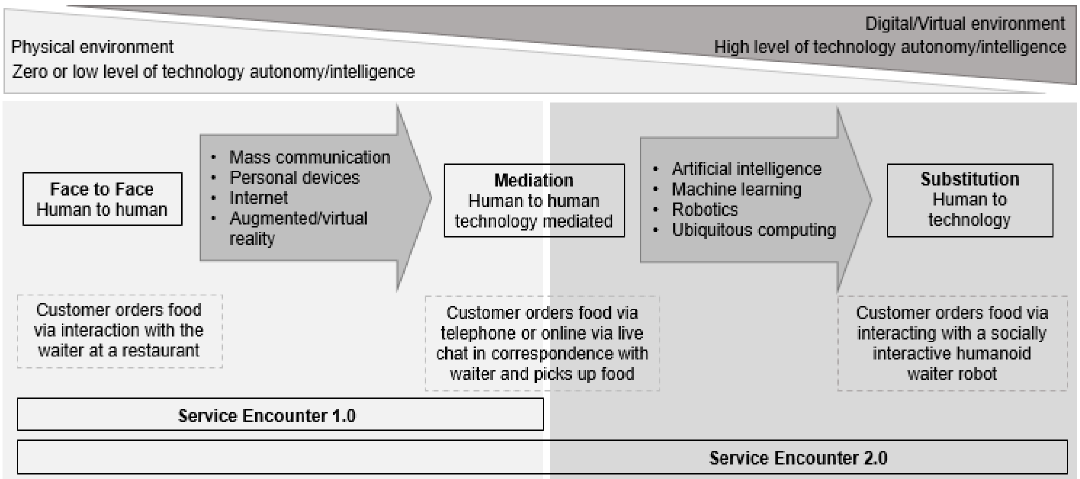
Although the definition of a service encounter 2.0 includes interactions enabled by complex service systems and is not restricted to one-on-one service frontline interactions, these studies show that, even in the service encounter 2.0 environment, a customer’s perspective of the core service delivery at a distinct point of contact is of high interest. Technology may augment or substitute service employees in delivering service to a customer. Owing to these technological possibilities, the spectrum from face-to-face interactions toward customer-to-robot interactions is one of the most radical changes in service delivery. Thus, this interaction type is of high relevance and is a prime example for the need of re-evaluating standing service encounter theories and their underlying premises. Following, I will describe the technological advancements that have enabled the evolution of service encounter 1.0 to 2.0. To organize the following explanations, I refer to Figure 3.

Service interactions have evolved from face-to-face interactions between two humans toward technology-augmented interactions. The technologies used in these interactions are not yet smart or autonomous; they merely mediate or augment the interaction between a service provider and a customer (Bitner et al., 2000; Schumann et al., 2012). For instance, this stage entails augmented service interactions enabled by augmented reality devices (Hilken et al., 2017). A service provider can use technology to improve customers’ service experiences. For instance, Porsche offers customers the additional service to see the mechanical details of an engine when buying a new Porsche through augmented reality glasses. At its core, this is still an interaction between two human actors and it is therefore a service encounter 1.0. Nonetheless, this stage marks the change toward service encounters 2.0 as the importance of the physical presence of both parties during the interaction diminishes (Bolton et al., 2018) and the service interface changes (Wirtz et al., 2018). For instance, a customer orders food by calling a restaurant's staff and collects it later, and Apple support offers customers live chat with the service staff via the Internet. Further, remote and interactive smart services occur on the verge of physical and digital realms as a customer directly interacts with a product; however, the service provider is digitally connected to a customer. For example, the gallbladder of a patient in France was successfully removed via the use of surgical robots by doctors who operated the robots from the U.S. (Minkel, 2019). Moreover, through advanced software and hardware, customers and employees can interact in completely virtual worlds by embodying personalized avatars (De Keyser et al., 2019). Thus, the service interface is gradually becoming more technology-dominant (Larivière et al., 2017).

The second evolutionary stage is enabled by technologies such as AI, machine learning, as a subset of AI, as well as robotics and ubiquitous computing (Huang & Rust, 2018; Marinova et al., 2017; Wirtz et al., 2018). Service delivery increasingly occurs in a digital setting, and the service interface is becoming technology-dominant. Thus, the level of frontline technology infusion is rising.

In both physical and digital environments, some forms of technology-substituted interactions have long been established. For instance, software developments have led to widespread availability of self-service terminals in various service offering such as ATMs or self-service checkin desks at airports (Schumann et al., 2012). The Internet, personal computers, and smartphones enable online banking and online shopping.

However, more sophisticated, *human-like* forms of automated service interactions are now also possible. With the development of sophisticated AI that is able to learn autonomously from previous interactions and that mimics human communication styles, technology is increasingly becoming a more autonomous counterpart to customers (Marinova et al., 2017). Thereby, AI refers to a set of computer science techniques that enable systems to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and language translation (Berlucchi et al., 2016). By implementing AI software in service robots defined as system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to a firm's customers (Wirtz et al., 2018) service encounters can occur without human touch in physical and digital environments. With the continual improvement of AI software, service robots may soon be able to take over most tasks previously carried out by humans and that require intuitive and empathic intelligence (Huang & Rust, 2018). For instance, in the physical environment, voice-operated digital assistants such as Alexa can help us to organize our daily lives. Socially interactive humanoid service robots such as iRobi can be placed in various service settings, for instance, as a teaching assistant at school (Broadbent et al., 2018) as well as in elderly care (Čaić et al., 2018). In the digital environment, new interaction possibilities are emerging owing to advancements such as robo-advisors; their financial advice is purely based on algorithms without human intervention. Another example is smart chatbots that answer customer questions automatically and autonomously and learn from their encounters. These new interactions enabled by this technology surpass the service encounter 1.0 definition as one human actor is replaced by technology.



Note. Developed based on De Keyser et al., 2019; Larivière et al., 2017; Marinova et al., 2017; Solomon et al., 1985; Wirtz et al., 2018; Wünderlich et al., 2013.

Figure 3: Outline of the Evolution from Service Encounter 1.0 to 2.0

2.3 Theory Evaluation

In the following sections, I will first identify the most relevant service encounter 1.0 theories. Then, adapting Bacharach's (1989) approach, introduced in Section 2.2.1, I develop an evaluation scheme. Finally, I deploy the evaluation scheme by performing an exemplary evaluation of the most relevant service encounter 1.0 theory.

2.3.1 Identification of Relevant Service Encounter 1.0 Theories

To identify relevant service encounter 1.0 theories, I built on Furrer et al.'s (2020) work. They analyzed the content of more than 3,000 articles published in 10 major academic journals for service research in the past 27 years and found 385 articles that focused on studying service encounters. By granting me access to their database, I was able to use their literature review as a foundation for my analysis. Since researchers have recently called for the revision of theories and the development of new theories (e.g., Kunz et al., 2019), it may be assumed that new research still relies on service encounter 1.0 theories. Nonetheless, I excluded all articles published after 2012 since, from this year on, service research was on the verge of conducting studies in the service encounter 2.0 environment (e.g., Schumann et al., 2012), so as to identify the most relevant service encounter 1.0 theories. I systematically analyzed the remaining 198 articles for their theoretical bases and counted the number of articles that used the same theoretical foundation. Of the articles, 61 were exploratory or did not explicitly state an underlying theory. Another 62 identified theories were coded as *other theories*, since they were not applied in more than one article. Nevertheless, some of the one-time mentioned theories could be clustered under a joint theme. The remaining 75 studies did apply a clear theoretical basis. Role theory and attribution theory could be identified as very relevant theories in service research, followed by social exchange theory, appraisal theory, the theory of reasoned action, and the expectation/disconfirmation paradigm. The result of this review is presented in Table1.

Main theories	Count	Seminal reference(s)
Role theory	19	Broderick (1999); Solomon et al. (1985)
Attribution theory	14	Kelley (1967)
Social exchange theory	7	Homans (1958); Emerson (1976)
Appraisal theory	6	Folkman and Lazarus (1980); Roseman and Smith (2001)
Theory of reasoned action/ theory of planned behavior	6	Ajzen & Fishbein (1973); Ajzen (1991)
The expectation/disconfirmation paradigm	6	Parasuraman et al. (1985)
Affective response theory	4	Mattila and Enz (2002)
Justice theory	3	Park et al. (2008)
Emotional contagion	2	Hatfield et al. (1994)
Emotional labor	2	Hochschild (2012)
Service-dominant logic	2	Vargo and Lusch (2007)
Arousal theory	2	Steenkamp and Baumgartner (1992)
Flow theory	2	Csikszentmihalyi (2000); Koufaris (2002)

Other theories		**Example theory and reference**
(Behavioral) economic theory related	13	Equity theory (Ruyter & Wetzels, 2000); Prospect theory (Daniel Kahneman & Tversky, 2013)
Emotion theory related	8	Socioemotional selectivity theory (Carstensen et al., 1999); Interpersonal theory of emotions (Parkinson, 2006)
Cognition theory related	6	Cognitive dissonance theory (Harmon-Jones & Harmon-Jones, 2007)
Relationship marketing theory related	5	Relationship marketing theory (Berry, 1995)
Culture theory related	3	Theory of national culture (Hofstede, 1983)
Resource theory related	2	Resource dependency theory (Pfeffer & Salancik, 2003)
Other theories	25	Queuing theory (Gross et al., 2008); Practice theory (Cetina et al., 2005)
Theory not stated/exploratory	61	

Table 1: Overview of Relevant Service Encounter 1.0 Theories

2.3.2 Theory Evaluation Scheme

As outlined above, the explanatory relevance of theories is bounded by spatial and temporal boundary conditions (Bacharach, 1989). Further, theories should be constructed in a way that they can answer questions of why, when, and how concerning the processes and outcomes of service encounters 2.0. Only then may they predict and explain phenomena in the service encounter 2.0 environment. In this section, I develop the evaluation scheme, which consists contextual and individual boundary factors of service encounter theories in the service encounter 2.0 environment.

2.3.2.1 Contextual Factors Bounding Service Encounter 1.0 Theories

The contextual factors of service encounters 2.0 that have changed dramatically since the development of service encounter 1.0 theories are the *servicescape* and the *service interface* (e.g., Wirtz et al., 2018). The servicescape changes premises concerning *how* and *when* service encounters take place, while the service interface affects *how* service is delivered.

First, the *servicescape* is defined as „[...] the manmade, physical surrounding as opposed to the natural or social environment [...]" (Bitner, 1992, p. 58). In the early 1990s, the typical service environment was a physical space in which service was delivered to customers. As outlined above, technological advancements have created multiple spatial possibilities to deliver service to customers (Bolton et al., 2018). For instance, the digital assistant Alexa is mostly placed in private homes. Customers can utilize their smartphones almost anywhere to shop online, talk, or chat to (human and artificial) customer advisors. Further, supported by virtual reality or augmented reality technologies, service firms can not only create new online channels but can augment existing or virtually create artificial, personalized service environments. Also, via the Internet, customers have access to these new servicescapes 24/7. These various new options when designing a servicescape are relevant for spatial and temporal assumptions that underlie service encounter theories. The previous premises of service encounter 1.0 theories that service encounters usually happen in a physical environment during office hours no longer hold. This affects their explanatory relevance concerning behavior determination, since the service environment has a specific effect on how customers behave in service interactions. In a private space, socially desirable behaviors play a less important role than in retail stores where other customers are present (Grove & Fisk, 1997). Thus, new servicescapes that enable service interactions in *various places* (physical and virtual) and *at various times* constitute contextual factors that bound service encounter 1.0 theories.

Second, with new possibilities of technology infused service interactions, customers can choose between human and artificial *service interfaces.* An artificial interface can take various forms (De Keyser et al., 2019), for instance, it can be a virtual agent (e.g., Jamie, ANZ's digital service advisor), a voice-regulated black box, however representing a female service assistant (e.g., Amazon's Alexa), or a photo attached to an online chat box that simulates a chat (e.g., Bank of America's chatbot Erica).

Wirtz et al.'s (2018) definition of service robots includes digital agents and embodied robots. These robots can vary in their appearance, for instance in terms of their anthropomorphism, gender, and responsiveness. Thus, the service encounter 2.0 may be realized via different interface *mediums,* in various forms of *service robot design* equipped with different levels of *automated social presence* and *agency*. Thus, service encounter 1.0 theories are bounded by the temporal assumption of theorists at the time of their development in that service may be delivered directly or indirectly via a human interface. Conclusively, they are also bounded by assumptions about a service provider's cognitive and behavioral capabilities as well as by customers' responses to their behaviors.

The new *interface* mediums as well as a *robot's design* change how human's respond to their service delivery counterpart. Although the effect that humans respond socially to robots has been well established in lab settings (Katz & Halpern, 2014;

Nass & Brave, 2005), this is only true for very specific social robot types. Humans tend to use the same shortcuts for social responses when interacting with robots that trigger social cues, for instance through a human voice (Nass & Brave, 2005). These responses are nonconscious and automatic. Thus, humans rely on social norms and politeness in interactions with socially interactive service robots. However, in service encounter 2.0 environments, there are several new opportunities for service interfaces.

Further, people make assumptions about a robot from its physical *design* (Nomura et al., 2006). For instance, human characteristics are attributed to very anthropomorphic-looking robots (Epley et al., 2007) and seem to evoke more trust in human (Waytz et al., 2014) than nonhuman-looking robots. Moreover, service robots' appearance affects how people interact with them. For example, it is increasingly noticed that customers talk to smart digital assistants such as Amazon's Alexa differently than to a human assistant. They rather give short commands and tell directly what they want (West et al., 2019). Thus, it can be assumed that service robots evoke a new form of interaction and communication in which humans adapt to a robot's communicative skills and develop new interaction norms. Further, research suggests that interactions with robots trigger parts of the brain that activate *theory of mind* assumptions, even though this effect is stronger in human interactions (Rilling et al., 2004). That is, in an interaction, humans assume that their robotic counterpart has a mental state, a theory about the world that influences its behavior. With increased accuracy of *automated social presence* (van Doorn et al., 2017), this effect should increase. Automated social presence is defined as the degree to which a human feels in the company of another social entity when interacting with a technological device (van Doorn et al., 2017). Thus, via new forms of communication and interaction with service robots in service encounter 2.0 environments, the two counterparts' behaviors cannot be described by social norms that used to be consulted for interactions between two human counterparts in service encounter 1.0 environments.

Agency is defined as an entity's ability to reflect on and act reflexively toward a social environment (Archer, 2000). By reflecting on past experiences, entities with agency adapt to their social surroundings and affect their sociocultural context through their presence and behaviors. At the same time, the sociocultural context sustains them (Jenkins, 2008 cited by Neff & Nagy 2016). In these terms, it can be argued that very sophisticated, autonomous, and self-learning service robots have agency. However, machines reflect on their own experiences via previously defined reflection mechanisms that are not their own but are programmed by their human developers. Thus, they do not really subjectively reflect on and adapt to situations. Nonetheless, Novak and Hoffman (2019) argue that smart and connected technological interfaces may be able to autonomously and independently (without authority) interact with customers, thus taking on an actor role in service encounters enabled by *machine agency*. The question whether service robots have agency and are thus able to co-create value in service encounters in the same ways as persons has rarely been empirically studied in service literature. Although there has been first research into value co-creation and co-destruction in elderly care networks (Čaić et al., 2018), it cannot be concluded that humans and robots' value creation processes are the same. It is unclear how customers perceive service robots' behaviors which are guided by sophisticated, very realistic, self-learning AI. Some behaviors of service robots may even be perceived as creepy (Wang et al., 2015) and may lead to value co-destruction compared to when a person acts out these behaviors. Thus, machine agency cannot be equated with human agency. It can therefore not be assumed that explanations and predictions of processes and outcomes of service interactions via service encounter 1.0 theories by assumptions about actors with agency who for instance adapt to their physical surroundings can still explain and predict the same phenomena in the service encounter 2.0 environments.

The assumption about a human interface in a physical service environment in service encounter 1.0 theories cannot be transferred one-to-one to interactions with other entities such as service robots in the service encounter 2.0 environment. The physical appearance as well as the behavioral and social cues given by interfaces in various service encounter 2.0 environments may not trigger the same schemas and mental models as humans in customers. The effects of these changes on service encounters can only be accurately predicted and explained by theories that fit our digital age.

2.3.2.2 Individual Factors Bounding Service Encounter 1.0 Theories

Bacharach (1989) stresses that theorists need to state their theory's boundaries concerning which states a theory covers and does not cover. A clear narrative that describes the subspace of the conceivable spatial and temporal states a theory covers are often missing, because it is hard to account for all possibilities. For instance, individual reactions to service delivery in the service encounter 2.0 environment (e.g., nonhuman counterparts) differ to those imaginable by most theorists before the 1990s.

Thus, the *how* and *why* service interactions take place have changed. Further, for the adoption of and interaction with new technologies in service encounters, customers' willingness to co-process is crucial (Heidenreich & Handrich, 2015). I argue that, in technology-infused service interactions, this willingness to co-process depends on customers' *skills* to use and *attitudes* toward new technologies that enable service encounters 2.0. Thus, they must be accounted for as boundary conditions of service encounter 1.0 theories.

Concerning *skills*, some people are afraid to interact with new technology, since they fear that they will make mistakes and do not believe they have the skills set (e.g., communication skills, understanding of algorithms and mechanical reasoning) to use the technology right (Parasuraman & Colby, 2015). Thus, for service encounters 2.0, the customer requires different interaction skills than in service encounters 1.0, where more natural human interaction dominates an encounter.

Concerning *attitudes*, people (including theorists) *know* about properties of things (e.g., service robots) in the world through their perceptions of them. These perceptions may be more or less true. The way in which we perceive a property at a point in time (our representation of it) is called an attribute, and it influences our attitude toward the object (Bunge, 1977, 1979 cited by Weber, 2012). These perceptions are shaped by the individuals' values toward and experiences with the object. Humans have protected *values* such as the values of privacy, honesty, authenticity, and mutual respect (Baron & Spranca, 1997). These values may be broken by interactions with other entities and may therefore shape attitudes toward and motivations to engage in technology-infused service encounters (Turkle, 2007). For instance, relationships to entities enabled by automated social presence are distinct phenomena from customer-provider relationships or relationships with nonhuman artifacts (van Doorn et al., 2017). They may break the value of authenticity and privacy when people believe they are being deceived and fear that the collected data by the robot is not safe.

Further, *ethical aspects* must be discussed in terms of data use, privacy, and level of autonomous decision-making of machines, which affect customers' attitudes toward new service encounter 2.0 interactions (Wirtz et al., 2018). Through media coverage, a dystopian picture has been created of AI, which negatively influence people's perceptions of service interactions with service robots (Sparrow & Sparrow, 2006). People spread fear about machines becoming intelligent, taking over jobs and intruding on their privacy. Some claim that, owing to the automation of daily interactions, service interactions are being dehumanized (Ostrom et al., 2015) and are afraid to lose control over the machines and the long-term effects of more and more robots in our lives. The increased automation further leads to fears of job losses. Here, people consider not just their own jobs, but also of beloved service providers and impacts on the job market in general. This in turn leads to less trust and openness and thus negative attitudes toward (smart) technology devices.

Moreover, Dietvorst et al. (2015) show that humans experience *algorithm anxiety* when machines make decisions for them and trust a person more, even when they have experienced that person making a mistake. Customer resistance to smart technologies is also partly explained via *psychological barriers* and general skepticism toward smart technologies. This means that some customers are generally skeptical toward (smart) technology and may simply refuse to interact with a smart object in service delivery (Mani & Chouk, 2018). The skills and attitudes and their effects on human behaviors not yet fully known in human-to-human interactions must be accounted for when exploring interactions in the service encounter 2.0 environments, since they describe theoretical boundary conditions of service encounter 1.0 theories.

The contextual and individual bounding factors identified in this and the previous section (see Figure 4) may not all affect all underlying assumptions of service encounter 1.0 theories. Rather, each theory's theoretical assumptions must be critically identified and evaluated with respect to these bounding factors. Such an evaluation will now exemplarily be performed with role theory in the following section.

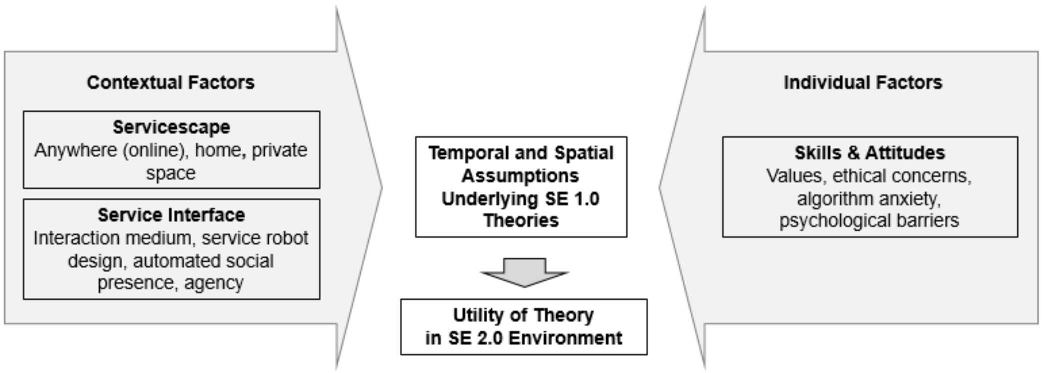


Figure 4: Outline of the Evaluation Scheme for Service Encounter 1.0 Theories

2.3.3 Exemplary Evaluation with Role Theory

Role theory was identified as the most relevant theory in past service research. Deploying the developed evaluation scheme, I will evaluate the underlying assumptions of the theory for their contextual and individual bounding factors, relying on a specific example of a service encounter 2.0 between a socially interactive humanoid service robot and a human customer.

Role theory makes a fundamental contribution to understanding the interpersonal dimensions of service encounters and is generally defined as a scientific approach to “study behaviors that are characteristics of persons within contexts and with processes that produce, explain or are affected by these behaviors” (Broderick, 1999). This theoretical approach emphasizes that persons are social actors who learn behaviors appropriate to the positions they occupy in society (Solomon et al., 1985). Thus, individuals gather a fairly standardized behaviors set over time. The appropriateness of enacting these behaviors in a role is learned from previous experiences with regards to social consensus, education, and/or professional training. Role theory relies on four key elements: role script, internal roles set, role performance, and role congruence (Broderick, 1999; Solomon et al., 1985). Relying on Broderick (1999) and Solomon et al. (1985), I will now describe these elements in some detail.

According to Solomon et al. (1985), *role scripts* are behaviors that are expected, enacted, or developed in service delivery and may be described as a coherent sequence of causal events. The demands on the role play are defined by the environment and are context-specific (Solomon et al., 1985). For instance, the role of a customer in a fine dining restaurant differs to that in a fast food restaurant. Further, a role player’s behavior according to the script is interdependent with the counterpart’s behavior. To appropriately react to one’s counterpart, it is crucial that people have the ability to empathize with their counterpart and take their perspective. Additionally, by analyzing the counterpart’s behaviors and common service settings, implied behavioral expectations are derived. The derived expectations change among encounters and are moderated by a person’s characteristics, cultural background, and perceptions as well as situational factors such as time, place, and service environment. It is crucial that both counterparts in service interactions read from a common role script. The *internal roles set* is a behaviors set established through working relationships and an understanding of individual role commitments in service provisions (Solomon et al., 1985). *Role performance* entails the cumulative behaviors and actions performed by those involved in a service interaction to fulfill their roles in the encounter. It is the de facto enactment of the behaviors believed to be appropriate read from the role script (Solomon et al., 1985). *Role congruence* is achieved when there is a clear understanding of role expectations and if the expectations are fulfilled in the service interaction.

This congruence is mutually achieved between the counterparts and depends on well-defined and appropriate roles. In a service setting, role congruence is a two-dimensional issue of intra-role and inter-role congruence. *Intra-role congruence* is the extent to which a person's conception of their role is congruent with the counterpart's conception of that role. If missing, people are unsure of what behaviors others expect from them in their role. It thus describes the extent of the inner role clarity of a person. *Inter-role congruence* describes the extent of agreement between both counterparts in a service interaction concerning the appropriate role behaviors to be expressed. A lack of clarity affects the efficiency of an encounter. To become clear about their own role expectations, a counterpart must understand the other's role. Here, the first impression is pervasive. Customers look for hints and tangible signs of the counterpart's capability to deliver service to their expectations and assign them their role accordingly. Thus, the first interaction marks a critical assimilation phase and sets the basis for future encounters, which strongly effects the nature and tone of the interaction (Solomon et al., 1985).

From the elements constituting role theory, several underlying theoretical assumptions can be derived that bound the theory's explanatory power to explain service delivery processes and outcomes in service encounters 2.0. To evaluate these assumptions, I draw on the example of a service encounter 2.0 between a human customer and an embodied socially interactive humanoid service robot. This robot type is defined as an autonomous entity that can deliver service to their counterpart in a human-like way (Breazeal, 2004). Further, humanoid robots are designed with the aim to realize their hardware with human physical structure and properties (Yamane & Murai, 2018).

First, the theory assumes that a service interface is an actor who plays out their role in joint play with the customer. In terms of the joint play, it is crucial that the counterparts are in a common physical environment. With this robot type, service interactions most likely take place in a service firm's store. Thus, in terms of the *servicescape*, there are now bounding conditions in this service encounter 2.0 type as the robots are bound to a physical environment they can navigate in. However, concerning the *interface,* a socially interactive robot must be equipped with sophisticated software that allows the interaction to flow and the robot to autonomously decide on which behavior to play out. Thus, the robot needs to have an internal role set and the physical capabilities to play out the role in a way that allows role congruence to arise between the two actors.

In order for role congruence to emerge, the theory secondly assumes that the two actors understand their role expectations, give social cues, and can empathize with their counterpart, that is, they appropriately act out their roles in relation to the context and their counterpart. It may be argued that robots are able to act out role scripts, as they may be defined as learned, formalizable sequences of causal chains of behaviors that are easy to learn via machine learning (Schank, 1980) very evolved robot types may be able to mimic human behaviors astonishingly well (Haselton, 2018). Further, with increased *automated social presence* and machine *agency* ascription, socially interactive humanoid service robots may be recognized as social counterparts. Nonetheless, social cues as in human interactions may be read differently by customers when acted out by a robot. For instance, a robot’s attempt at small talk may not be experienced as an authentic and pleasant interaction. Also, persons do not ascribe the same level of warmth to a robot as to a human, partly owing to a robot’s physical incapability to be able to enact a level of warmth, e.g., with an authentic smile (Čaić et al., 2018) . Moreover, machine agency is not equally to human agency. Thus, one may conclude that robots cannot be seen as individual actors who have an individual view and impact on their social surroundings equal to a human actor with agency. Therefore, the robot *interface*, with its technological capabilities, is a contextual bounding factor for service encounter 1.0 theories.

The assumption of role theory about a natural social interaction between two actors in a service setting in which both parties communicate fluently must also be evaluated for individual boundary conditions. In some service encounters 2.0, customers need new interactions *skills*, for instance, when they must give precise commands to a technological device or must properly use a technological device to start an interaction. Concerning socially interactive service robots, this is not a strong boundary to the theory, since a customer may talk to a robot in a similar way as to a human counterpart and thus requires few additional skills. However, in order for role congruence to emerge, customers’ will have to learn to take the perspective of as well as to read behavioral (social) cues enacted by a nonhuman entity and understand their way of reasoning.

Further, role theory assumes that actors react to their equal counterpart and read social cues in a human, social way. Thus, they literally interact in a service encounter to co-create value by enacting their roles and communicating openly. In a service encounter 2.0 with a humanoid service robot, the assumption of open communication and two actors with agency who read the other's social cues and act accordingly is bounded by individual *attitudes* toward nonhuman entities. Humans have different attitudes toward robots than toward other humans. As outlined above, these are shaped by ethical concerns and individual properties such as personal values, algorithm anxiety, and psychological barriers (e.g., privacy concerns and general skepticism to interact with nonhuman entities; Baron & Spranca, 1997 Dietvorst et al., 2015; Mani & Chouk, 2018). This affects their trust in and openness towards an interaction (Dietvorst et al., 2015), which in turn affects their behavior toward their counterpart. Thus, they will share less information as well as fewer social cues and may not know how to act out their role toward a robot. Moreover, the attitude toward the counterpart strongly affects the nature and tone of the interaction. As one player identifies a role, the other's role is simultaneously defined, and behavior that is perceived to be appropriate is enacted. In an interaction with a humanoid robot, it cannot be assumed that the interaction follows common social norms. This challenges the assumption of the possibility of role congruence emerging through reading from a common role script and the customer's perception of the robot as equal to a human actor with agency. One may well assume that human customers do not act in the same way with a robot as with another person. Either new forms of interaction with robots emerge, or the theoretical assumptions about role congruence must be altered. An overview over the evaluation is outlined in Table 2.

Theoretical Assumption	Contextual Boundary Factors	Individual Boundary Factors
Direct interaction between *social actors* ▪ Actors have an internal role set/agency ▪ Actors are able to enact their roles in joint play ▪ Actors understand their role expectations	*Service Interface* (SI): ▪ Not all SI have an internal role set programmed or are able to learn & adapt ▪ Machine ≠ human agency ▪ Missing physical capabilities to act out their role	
Role congruence emergence through *taking the other actor's perspective* (emphasizing) – *appropriate* role play in relation to *context* ▪ Actors can show social cues ▪ Actors react to their counterpart & read social cues in a human, social way ▪ Actors read from a common role script	*Service Interface* (SI): ▪ Missing physical capabilities to show social cues ▪ SI cannot emphasize, not enough autonomy to react individually on customers' individual behaviors	Customer *skills*: ▪ Taking a non-human perspective; understand robotic reasoning ▪ Reading social cues of nonhuman SI Customer *attitudes* towards nonhuman actors: ▪ Impact on customers' openness & trust; give less information & social cues; unwillingness to co-process ▪ Lead to different perception of role; no common role script; different/new (social) norms

Table 2: Overview of Role Theory Evaluation for S.E. 2.0 with a Socially Interactive, Humanoid Service Robot

2.4 Discussion and Future Research Directions

In this conceptual paper, an evaluation scheme for service encounter 1.0 theories was developed to evaluate their fit as a theoretical foundation for service interactions in the service encounter 2.0 environment. To identify relevant service encounter 1.0 theories to be evaluated, I undertook an extensive literature review, identifying role theory as the most relevant service encounter 1.0 theory. In the development of the evaluation scheme the servicescape as well as the service interface were identified as contextual boundary factors for the underlying assumptions of service encounter 1.0 theories. Likewise, individual factors such as necessary skills to interact with and attitudes toward new technologies that enable various interactions in service encounter 2.0 environment, were identified. Thus, they impact past theoretical assumptions underlying service encounter theories.

This analysis contributes to literature in several ways. First, it provides an overview over the technological advancements and changed factors during the evolution from service encounter 1.0 to service encounter 2.0 (Figure 3), connecting several separate insights from previous research (De Keyser et al., 2019; Larivière et al., 2017; Marinova et al., 2017; Solomon et al., 1985; Wirtz et al., 2018; Wünderlich et al., 2013) in a comprehensive model.

Second, to my best knowledge, this is the first study to focus on identifying theoretical bases of service encounter studies through a systematic literature review. This thorough review gives scholars an overview over 20 years of theoretical foundations used in service research (Table 1).

Third, this research contributes to literature by developing an evaluation scheme (Figure 4) for these theories, in that identifying crucial boundary conditions in the service encounter 2.0 environment. The identified focal factors (i.e., the servicescape, the service interface, customer skills, and attitudes) allow researchers to develop new and to adapt existing theories about service interactions by evaluating the fit of the theoretical assumptions in relation to the factors.

Fourth, this conceptual work provides an evaluation of role theory (Table 2) for an interaction with a humanoid socially interactive service robot revealing that it is bounded by theoretical assumptions about capabilities of the service interface to act out their role and show appropriate behavioral cues. Further, it is bounded by customers' attitudes towards robots and the interpretation of nonhuman social behavior which in turn affects their willingness to co-process. In its evaluated form role theory may be applied as a theoretical foundation for service interactions in the service encounter 2.0 environment. Hence, the study starts of filling the identified gap of theory development in changed service environments (Kunz et al., 2019; Novak & Hoffman, 2019).

Although this work offers several new insights, some limitations have to be considered which constitute starting points for future research. First, the literature review only considered articles in the top ten service research journals in a limited timeframe. It can be argued that including more studies from other journals over a longer period of time may provide more concise insights into the theoretical foundations of past service encounter studies. Although I derived the identified contextual and individual factors in the evaluation scheme from a thorough literature review, more boundary factors may be relevant. For instance, with the continuous advancement of frontline service technology, new interaction forms will not be covered and lead to additional theoretical boundary conditions. Further, with technological advancements, some of the here identified boundary factors might be overthrown. For example, if designers are able to create robots that are indistinguishable from humans, the interface may no longer be a relevant boundary factor. Thus, this analysis itself is bounded by the author's temporal and spatial boundary conditions. Moreover, while I relied on seminal articles of the identified theories and their underlying assumptions, researchers have further developed these theories over time. For instance, social exchange theory has been applied in many disciplines, which have adapted the theory to their needs (Emerson, 1976). All these aspects should be considered when conducting further evaluations on theories and a thorough analysis of their definition and use in the literature provided.

The analyses undertaken in this research present opportunities for future research. Following, I provide a compilation of research questions I derived from this research.

- How far do theories need to be further adapted or newly evaluated to serve as a theoretical basis for all technology-infused frontline interactions, including interactions between autonomous smart technology devices (De Keyser et al., 2019)?
- Which other assumptions about service interactions and human behaviors form boundary factors for underlying assumptions of existing service encounter theories?
- Which new assumptions about service interactions and human behaviors arise in the service encounter 2.0 environment?
- What are the theoretical differences in explaining the differences between artificially intelligent social machines and humans? How can customer reactions such as surprise, delight, and behavioral responses (e.g., word of mouth) in a service interaction in the future be predicted and explained when triggered by an artificial intelligent, social, likeable machine compared to human?
- How do technologies attached to (e.g., smartwatches) or (in the future) implemented in the customer's body (e.g., smart contact lenses, brain chips) affect contextual or individual boundary factors?
- Which attributes do customers assign to different service robot types with various intelligence levels (Huang & Rust, 2018) and how do they differ from human service delivery (Wirtz et al., 2018)? What can theoretically be assumed about their influences on the service delivery process and outcomes?

- Do interactions with AI technologies represent a completely new form of interaction that cannot be explained by sociological or psychological theories but mark a new field of study? For instance, AI can be perceived as a human counterpart and as a technological device at the same time (Mick & Fournier, 1998).

2.5 Conclusion

"Together with globalization, the influence of technology on service is the most profound trend affecting services marketing today" (Bitner, 2001). Mary Jo Bitner made this statement at the beginning of the 21st century. Almost two decades later and at the verge of the fifth industrial revolution (Schwab, 2017) , technology is not just a variable to account for in specific cases. It is the new norm. The daily lives of customers and employees are infused with technologies. These technologies are developing at a breakneck pace and are becoming smarter and more sophisticated by the minute. Thus, the environment we live in is continuously changing, forcing us to continually learn and adapt. Transformation has become a constant in service environments. Yet, service research still relies on theories build in the last century. It is not clear whether the theoretical bases researchers typically relied on in the past still have enough explanatory power for the mechanism that underlie these new service encounters. Hence, this research helps to evolve service research into a new age. All identified factors should be considered and frequently reconsidered when evaluating and developing theories suited to the digital age as well as when conducting research in this new environment. Researchers will thus make more sustainable predictions as well as explanations of phenomena in the digital age paradoxically by constantly re-evaluating and adapting their underlying assumptions.

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3. A Transdisciplinary Review and Framework of Consumer Interactions with Embodied Social Robots: Design, Delegate, Deploy[4]

Abstract

Social robots are gradually entering the organizational frontline, and research is beginning to unveil the implications for consumer–firm interactions. While empirical studies on human–robot service interaction (HRSI) are scarce in business literature, other scientific fields have generated an abundance of empirical findings that can inform consumer research on successfully integrating embodied social robots in consumer-facing services. In this light, a systematic literature review was conducted across scientific fields, screening over 13,500 research articles. Through a thorough review process, 199 service-relevant *empirical* research articles were identified. Emanating from this data, an organizing meta framework is advanced (D^3: design, delegate, deploy). Leveraging this D^3 framework, a comprehensive overview of several dimensions of the literature is provided, and key insights for each framework dimension are presented. Based on this overview, implications for whether, how, and when to integrate social robots in practice and a comprehensive future research agenda are developed.

Keywords: Systematic literature review, Human–robot service interactions, Embodied social robots, Consumers, Future research agenda

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3.1 Introduction

Social robots are increasingly being deployed in a wide variety of consumer-facing services, where they co-create value with and for the benefit of the consumers they interact with (Lu et al., 2020; Wirtz et al., 2018). Robots welcome customers to restaurants and hotels, entertain children, and read cooking recipes at home, give additional information about products in stores or assist the elderly with walking to support their health (Henschel et al., 2021; KPMG, 2016). What all these robots delivering services to consumers have in common is that they represent an "information technology in a physical embodiment, providing customized services by performing physical as well as nonphysical tasks with a high degree of autonomy" (Jörling et al., 2019, p. 405). This integration of robots into the marketplace reshapes service interactions and also challenges some fundamental principles of consumer–firm interactions (Kaartemo & Helkkula, 2018; Subramony et al., 2018). While service robots come with different levels of intelligence (Huang & Rust, 2018) and in various manifestations (Wirtz et al., 2018), embodied robots engaging in social interactions with consumers are expected to ignite what could be the most dramatic transformation of the consumer service landscape in the age of service robots (Mende et al., 2019).

Thus far, research on the integration of embodied social robots in consumer-facing services is predominantly of conceptual nature (Čaić et al., 2019; De Keyser et al., 2019; Larivière et al., 2017; Lu et al., 2020; Subramony et al., 2018; van Pinxteren et al., 2020; Xiao & Kumar, 2021). As a consequence, calls for studies of success drivers for the integration of artificial intelligence-based technology, such as social robots, into services are repeatedly echoed as a chief research priority (Paul & Bhukya, 2021; Subramony et al., 2018; Wirtz et al., 2018). Seminal service work has yet to empirically explore consumer interactions with embodied social robots in general (e.g., Kim et al., 2019) or in particular contexts, such as hospitality (e.g., Sungwoo Choi et al., 2019), healthcare (e.g., Lee et al., 2017), food and status consumption (Mende et al., 2019), and elderly care (Čaić et al., 2018).

Meanwhile, empirical research on human–robot interactions (HRI), in which humans and robots coordinate their actions face-to-face in real time and in a shared environment (Dautenhahn, 2007), has been widely conducted in other scientific disciplines. For instance, it is well represented in fields such as robotics (e.g., Torta et al., 2014), medicine (e.g., Chita-Tegmark et al., 2019), information systems (e.g., Mettler et al., 2017), and psychology (e.g., Gallimore et al., 2019). The respective empirical findings amount to a wealth of knowledge on various social robot types interacting with consumers in different service contexts, studied with diverse scientific methods. Synthesizing the results of these studies promises implications for the design of successful interactions between consumers and social robots in service settings in general.

Because HRI is a growing multidisciplinary field, a variety of systematic literature reviews have been produced. However, none has been transdisciplinary in nature and taken a service focus. Most reviews have restrictive foci: nonverbal robotic communication (Saunderson & Nejat, 2019), emotions in HRI (Stock-Homburg, 2022), service failure (Honig & Oron-Gilad, 2018), first encounters (Avelino et al., 2021), ethical considerations related to HRI (Boada et al., 2021; Tan et al., 2021), social acceptance of robots in different occupational fields (Savela et al., 2018), social robots to combat loneliness (Gasteiger et al., 2021), or quantifiable evidence of human attitudes toward social robots (Naneva et al., 2020). Others have been restricted to a specific social robot model (i.e., NAO; Robaczewski et al., 2021) or context, such as elderly care (i.e., socially assistive robots [SAR]; Kachouie et al., 2014; Vandemeulebroucke et al., 2021; Wang et al., 2022), education (Woo et al., 2021), or hospitality (Ivanov et al., 2019).

Our extensive literature search identified four notable exceptions of literature reviews adopting an unrestrictive view of consumer interactions with robots. However, Lu et al. (2020) and Xiao and Kumar (2021) both predominantly derived their inferences from conceptual articles restricted to marketing and business outlets and thus based their implications on only a very limited set of empirical findings. Ameen et al. (2021) offered a comprehensive literature review of HRI across scientific disciplines, which did not, however, focus on consumer interactions with embodied social robots per se, but rather with smart technology in general. Finally, Lambert et al. (2020) included research articles in which users did not interact with social robots in service contexts and offered no structuring framework. An overview of existing HRI reviews in different scientific fields is depicted in Appendix A.

In summary, while the existing reviews each provide an overview of the HRI context of their particular focus and, in part, provide structuring frameworks, they mostly reveal a narrow perspective, either with respect to the literature stream they source from (e.g., marketing literature), the focal topic (e.g., service failure), or the robot types they studied (e.g., SAR). In consumer and marketing research, in particular, empirical research on consumers' interactions with social robots that are suitable for deployment in services is in undersupply compared to studies on other technologies, such as the Internet of Things (Kasilingam & Krishna, 2021; e.g., Nguyen & Simkin, 2017) or augmented and virtual reality technologies (e.g., Hilken et al., 2017; Shahab et al., 2021). Thus, we extend previous knowledge by reviewing the extant HRI literature from an all-encompassing perspective. We identified and mapped the empirical body of state-of-the-art knowledge on consumer interactions with social robots across scientific fields, developed a new and integrative framework to synthesize the literature on HRI in consumer-facing service contexts, and pinpointed future research avenues around consumer-facing service interactions.

3.2 This Review

The focus of this review is on human interactions with autonomous, embodied social robots providing services for and in co-creation with consumers, which we coin human–robot service interactions (HRSI). While established definitions of service robots in the business literature include autonomous smart objects (e.g., autonomous vacuum cleaners and self-driving cars; (Jörling et al., 2019; Wirtz et al., 2018), the current systematic literature review aims to synthesize empirical findings on robotic complements or substitutes for employees in consumer-facing service contexts. Therefore, we reviewed only studies on embodied and autonomous robots that can interact socially with consumers. Because such robots are able to exhibit nonverbal and verbal cues to express emotions and intentions in a human-like manner (Breazeal, 2004), consumers accept them as peers and interaction partners (Fong et al., 2003). Hence, such social robots can be effectively integrated into services, where they augment or substitute service employees (Čaić et al., 2019).

Considering the wealth of empirical studies on HRI in consumer-facing service contexts in different scientific disciplines, paired with the paucity of systematic reviews of extant research on actual consumer psychological and behavioral responses to interactions with embodied social robots, this study aimed to establish a comprehensive, transdisciplinary overview of empirical insights on HRSI. To this end, we undertook a systematic review of HRSI studies across scientific disciplines to structure the available information from a consumer research perspective around three central research questions:

1. *What overarching guiding structure organizes the extant HRSI literature?*
2. *What is the status quo of empirical insights on HRSI across scientific fields, and how can these insights be synthesized to inform researchers and practitioners on the successful integration of embodied social robots in consumer-facing services?*
3. *What future research avenues emerge from an integrative perspective on HRSI?*

3.3 Methodology

We employed a systematic narrative literature review following the key stages suggested by Siddaway et al. (2019). This approach represents the most informative, thorough, and well-justified method (Paul et al., 2021; Paul & Criado, 2020) of identifying relevant studies, with minimal biases and errors (Jesson et al., 2011), and for critically evaluating and integrating the search results (Siddaway et al., 2019). Our systematic review, in particular, encapsulates studies on human–robot service interaction across disciplinary boundaries to gain deep insights from the existing literature through a systematic and structured content analysis of the identified papers (Lim et al., 2021; Seuring & Gold, 2012). Thereby, we investigate the data according to various dimensions, such as methodology, study contexts, characteristics of robots and consumers, and key constructs (Paul & Rosado-Serrano, 2019).

Next, we discuss our review process according to two main phases: (1) the systematic search and data extraction process and (2) the systematic review and analysis process. While steps in the former phase pertain to data collection, steps in the latter relate to data screening, cleaning, and coding. Figure 5 provides a detailed summary of our systematic review process.

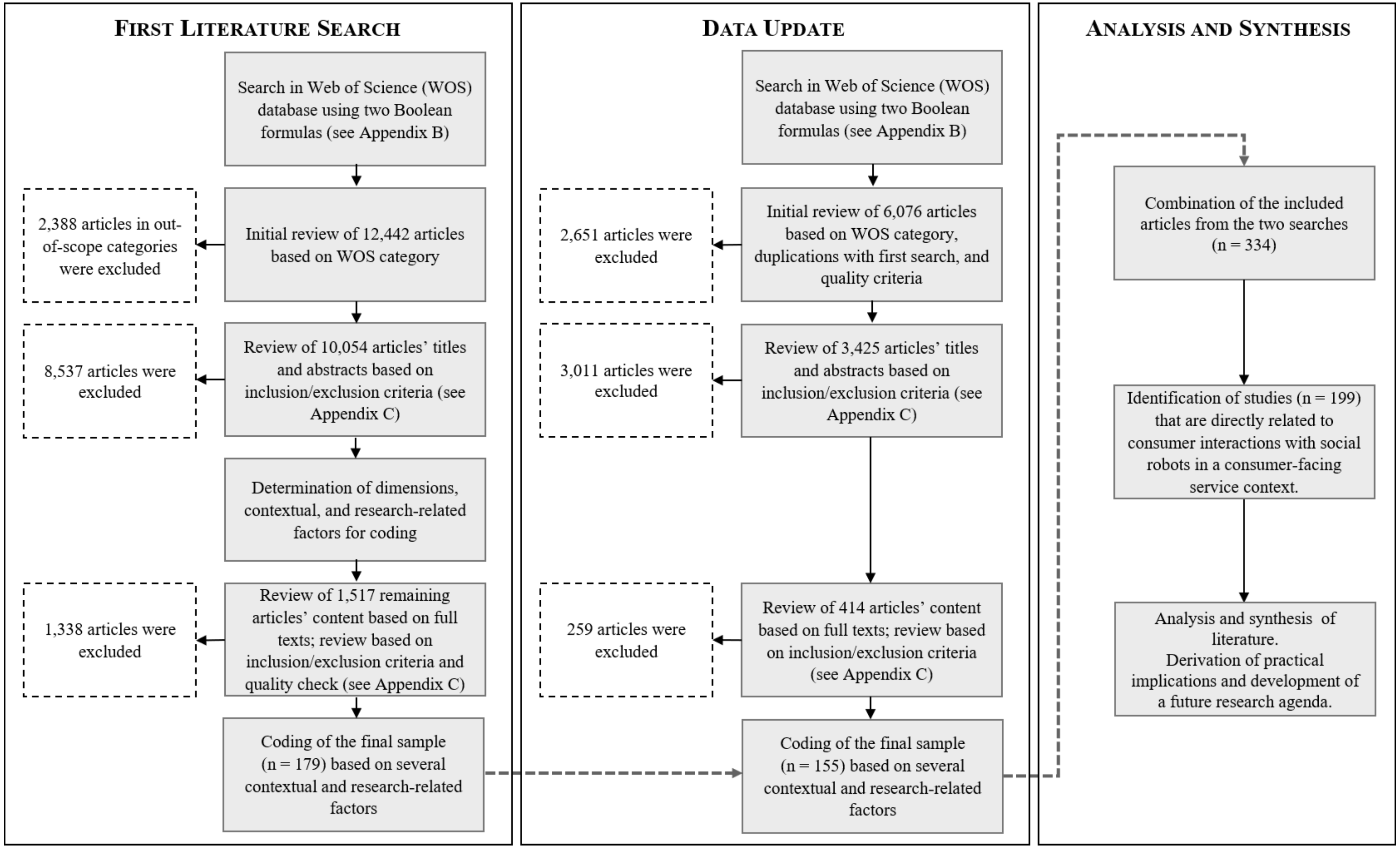


Figure 5: Systematic Review and Synthesis Process

3.3.1 Systematic Search and Data Extraction Process

Database search. The body of literature pertaining to robotics and HRI is broad in scope and incorporates a wealth of studies across a wide quality spectrum. In line with previous systematic reviews (e.g., Montoro-Pons et al., 2021), we employed the Web of Science (WOS) database to source only articles that reflect on our research questions and meet a minimum quality standard (e.g., Kapoor & Banerjee, 2021). The WOS database includes the main corpus of HRI research in diverse scientific fields published in scholarly qualified, peer-reviewed journals (Antons & Breidbach, 2018). Thus, in line with our inclusion criteria, WOS helps to avoid low-impact, non–peer-reviewed sources (Martín-Martín et al., 2018).

This review encompasses studies on consumer interactions with embodied social robots in a service context. Accordingly, we formulated Boolean phrases to systematically search the WOS database for suitable research evidence written in English (see Appendix B for a detailed overview). The first Boolean phrase included 28 terms used in prior literature to refer to robots deployed in different consumer-facing services, such as social robots, care robots, and assistive robots. We anticipated that in some neighboring disciplines (e.g., psychology, management), "robot" might also be used without further specification but still refer to social robots. Therefore, we developed a second Boolean phrase that included the term "robot*" on its own. With this phrase, we searched WOS again, focusing on selected categories (i.e., "psychology," "business," and "management").

The Boolean searches, conducted in May 2019, together revealed 12,442 articles (9,861 + 2,581), across 205 different WOS categories. After excluding WOS categories outside the scope of our review (e.g., astrophysics, physics, thermodynamics), 10,054 articles remained. Then, in November 2021, we updated our data and re-ran the Boolean phrases, which resulted in 6,076 additional articles. After excluding irrelevant WOS categories, duplicates to the first search, and articles published in journals that did not meet the quality criteria, we added 3,425 of these articles to the data set[5].

[5] The data for this literature review was updated last in November 2021. At this point in time, a great number of the articles included were published *online first* and are counted in our statistics as published in the year of their first online publication. Now (November 2022), the majority of *online first articles* have been assigned to an issue and are *referenced in this thesis according to their current status*. Hence, some references are e.g. indicated as published in 2022 but were published online first before November 2021.

Data extraction. We used self-developed data extraction sheets to warrant transparency in our data, search, and analysis processes and to provide a control mechanism for the entire systematic review process (Rashman et al., 2009). We merged all article information resulting from the different WOS searches into one spreadsheet, which then served as a basis for all screening, coding, and information extraction processes.

3.3.2 Systematic Review and Analysis Process

Initial screening. In the first screening round, two independent coders assessed each article's title. If an allocation based on title alone was not possible, they reviewed the abstract to determine if it fit the scope of our research (Calabrò et al., 2019). The intercoder reliability exceeded the suggested threshold of .70 for both the initial (I_r = .92) and updated (I_r = .94) data screening (Perreault & Leigh, 1989; Rust & Cooil, 1994). Articles that received inconsistent codes were screened by a third coder from the author team. In this step, we excluded 11,548 articles (8,537 from the first and 3,011 from the second search data set) because they were not empirical (e.g., conceptual papers, reports) or did not study human behavioral or psychological outcomes resulting from direct or scenario-based interactions with embodied social robots. For example, some of the excluded papers focused on technical and engineering issues (e.g., Kim et al., 2009) or scale development objectives (e.g., Banks, 2019). We also excluded studies involving individuals with specific needs or limited agency (e.g., patients with Alzheimer's disease, children with autism, infants < 5 years old) because such actors co-create value in fundamentally different ways. Following this initial screening of titles and abstracts, we consulted the full text of all remaining articles (n = 1,931). If they did not meet the inclusion criteria (see Appendix C for a detailed overview), we excluded them (n = 1,597).

Quality assessment. As a first measure for quality control, we included only peer-reviewed journal articles because the review process provides a quality control mechanism that validates the results that such articles afford (Ordanini et al., 2008). Using a conservative approach when excluding articles in fields for which the research team had less familiarity, we initially did not exclude any articles on the basis of journal quality. However, upon obtaining an overview in the full text coding process, we noticed substantial variance in scientific rigor across disciplines. Therefore, in line with other systematic reviews that investigate broad multidisciplinary fields (e.g., Follmer & Jones, 2018), we turned to other objective quality criteria, including the

WOS index, impact factor, Scopus CiteScore, and Scopus journal quartile, all of which apply to the relevant scientific fields. We then included only those articles published in journals that appear in the Science Citation Index Expanded (SCI-E), and Social Sciences Citation Index (SSCI), with impact factors and Scopus CiteScores exceeding 1.00 and a ranking in the first quartile in one of Scopus's scientific categories.

Coding. After this screening and quality assessment, the sample consisted of 334 articles. In line with previous systematic literature reviews (e.g., Babić Rosario et al., 2020), we first performed content analyses of these articles, coding them according to 13 dimensions: (1) aim of the study, (2) research method, (3) methodological nature (i.e., qualitative/quantitative), (4) sample characteristics, (5) study country, (6) study context, (7) robot brand/name, (8) robot type, (9) robot morphological characteristics, (10) independent variables, (11) dependent variables, (12) moderators and mediators, and (13) key findings. To determine if an article relates to HRI in a consumer-facing service context (i.e., HRSI), we categorized the underlying study contexts based on the North American Industry Classification System (e.g., healthcare, arts and entertainment; 2017). This effort revealed a total of 199 articles directly related to interactions of social robots and consumers in consumer-facing service contexts. All the codes were checked again by a separate coder from the author team, and any inconsistencies were discussed and resolved by consensus.

Bottom-up thematic analysis. Following previous transdisciplinary reviews (e.g., Rietveld & Schilling, 2021), we performed an inductive, bottom-up analysis of the final 199 articles to identify themes to structure HRSI literature. Inductive bottom-up approaches are especially suitable for producing an overall description of dispersed data compared to deductive top-down methods, which allow for more detailed analyzes of more closely related data (Nowell et al., 2017). This is in line with our aim to develop a new, integrative framework emerging from our transdisciplinary data. After familiarizing ourselves with the data through content analysis, we identified common themes to cluster the articles in our data set (e.g., robot appearance, robot nonverbal behavior, human vs. robot), which we iteratively synthesized until three overarching themes emerged that incorporated all previous subthemes (see Section 3.4). While we developed the themes without using a specific theory or framework as a blueprint, elements of the framework were drawn from previous work (Puntoni et al., 2021; Wirtz et al., 2018).

PRISMA protocol. Finally, as suggested by Siddaway et al., 2019), we confirmed the suitability of the review and analysis processes by checking all items on the PRISMA 2020 protocol checklist, except for preregistration (see Appendix D; Page et al., 2021).

3.4 Results

3.4.1 D³ as a Guiding Framework of HRSI Research: Design, Delegate, Deploy

With a bottom-up thematic analysis of the coded data, we developed a general, integrative framework to structure the HRSI literature (Figure 6) according to three overarching themes that emerged from the analysis of the 199 articles included in our review: *design*, *delegate*, and *deploy*.

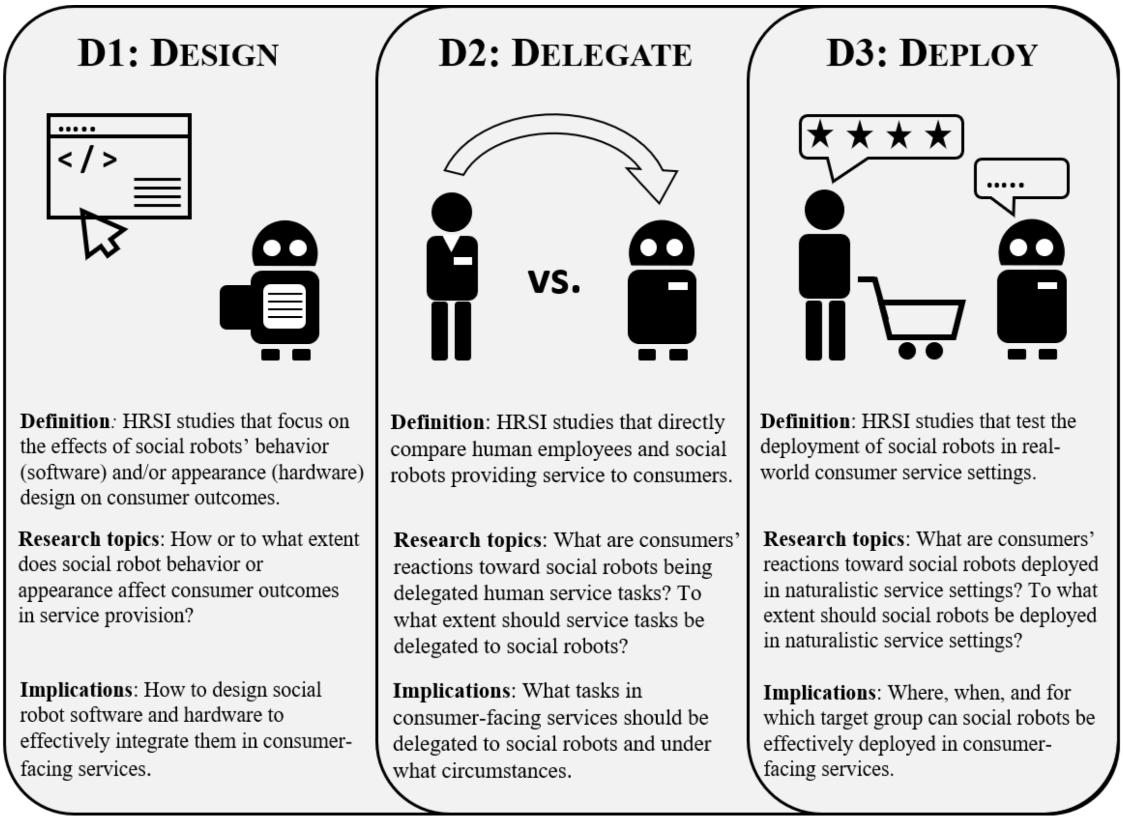


Figure 6: D³ Framework: Design, Delegate, Deploy

3.4.1.1 Design

A little more than half of the articles in our data set could be clustered under the design theme (n = 100 articles; n = 121 studies). Studies in these research articles aimed to understand the effects that the design of a robot's behavior (i.e., software) and appearance (i.e., hardware) might have on consumers. For example, studies of how a robot's behaviors, such as politeness (e.g., Lee et al., 2017), verbal or nonverbal emotion expression (e.g., Johnson & Cuijpers, 2019), and personality (e.g., Meerbeek et al., 2008), affect consumers fall under the design–software theme. Its design–hardware counterpart theme complements this perspective with a focus on how robot morphology (i.e., android vs. humanoid vs. machine-like; e.g., Qiu et al., 2020) or perceived gender (e.g., Stafford et al., 2014) inform consumer outcomes. Studies focused on design aspects mostly relied on lab or online experiments because they required high degrees of control.

3.4.1.2 Delegate

The 32 articles covering 52 studies clustered under the delegate theme directly compared human and robotic service provisions in efforts to determine how delegating service tasks traditionally performed by humans to social robots affects the perceptions and behaviors of consumers (Puntoni et al., 2021). For example, researchers have assessed the relative performance of robots versus humans, measured in terms of information comprehension (e.g., Palanica et al., 2019), performance of clinical tests (e.g., Desideri et al., 2019), or guidance of crowds (e.g., Kanda et al., 2008). These studies mostly relied on between-subjects lab, field, or online experiments.

3.4.1.3 Deploy

Finally, the third theme clustered 67 articles, including 77 studies of the deployment of robots in real-world settings. Rather than contrasting robots with human service providers, these studies attempted to establish the global effectiveness of social robots in consumer service environments. They might have compared robots being deployed across different environments (e.g., teaching science in an interactive laboratory or studio; Verner et al., 2016), offered general evaluations of a robot’s long- or short-term deployment (e.g., Serholt, 2018), or suggested effective ways to introduce robots to stakeholders in the field (e.g., Winkle et al., 2020). In line with their predominantly exploratory nature, these studies mostly relied on (longitudinal) field trials, based on observations, interviews, or case studies.

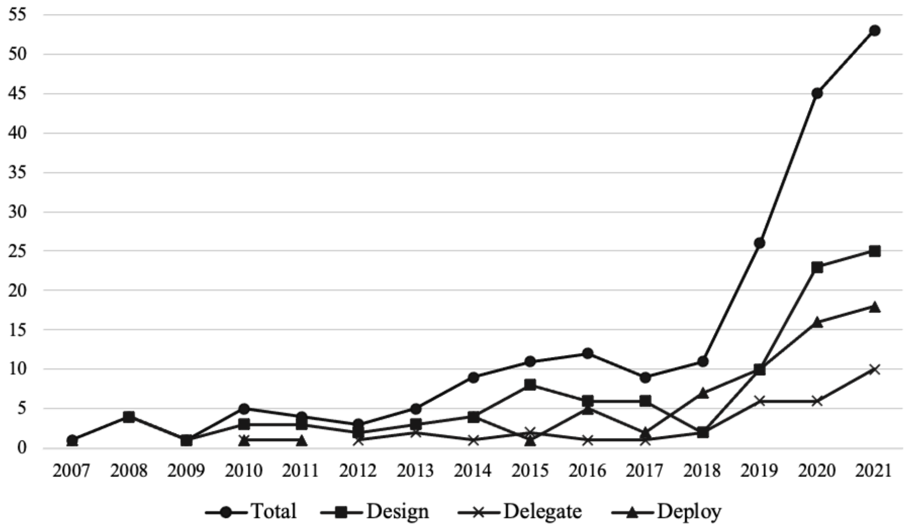
These three themes also build on one another, such that each theme provides implications for the others. Researchers and managers interested in consumer interactions with social robots might first consider a robot’s design aspects to predict their effects on consumers, then assess the effectiveness of delegating certain tasks in consumer service to a robot with this design before they finally deploy the robot to perform those tasks in a real-world environment.

3.4.2 Status Quo of Empirical Research on HRSI

In response to our second research question, we established the status quo of empirical insights into consumer interactions with social robots from a D^3 perspective. To this end, we first developed charts based on our descriptive analyses of (1) developments in article publications featuring empirical HRSI research over the years (Figure 7) and (2) the research fields represented in our data set (Table 3). To gain deeper insights into research settings, we next summarized and analyzed information on (3) the methods applied and sample characteristics, (4) the geographic regions for the data collection, (5) the study settings, and (6) the types of social robots used (Table 4). Finally, we provide (7) an overview of variables studied in the HRSI literature.

3.4.2.1 Publication Development

Concomitant with technological advancements in artificial intelligence (Huang & Rust, 2020) and mechanical engineering (Ghaffarzadeh, 2018), empirical research on human interactions with social embodied robots has increased significantly in the past decade (Figure 7). The first studies appeared at the beginning of the 21st century, but the majority of articles (84%; n = 167) in the final data set were published in 2015 or later. The topicality of HRSI is thus apparent: The years 2020 and 2021 (until November 7) account for 49% (n = 98) of all articles in the data set. The publication development is similar across all D^3 themes. However, the majority of articles under the delegate and deploy themes emerged from 2013 onward.



Note. The graph presenting the development of article publications over time includes articles published in 2021 up to November 7.

Figure 7: Publication Development in Total and by D^3 Framework Themes

3.4.2.2 Research Fields

This review includes articles from multiple disciplines and across a variety of research fields: 199 articles published in 81 journals spanning 47 WOS categories. We identified 17 clusters of WOS categories, highlighting the multidisciplinary nature of our final data set (see Table 3 for an overview). The three most represented categories—robotics, psychology, and hospitality—account for almost half (48 %) of the articles in the final data set. The other half encompasses diverse fields, including natural sciences (e.g., medicine, chemistry, physics), social sciences (e.g., business & management, sociology, behavioral science), humanities (e.g., arts, philosophy, ethics), and other service-related disciplines (e.g., education & educational research). Articles under the design and deploy themes are predominantly related to the robotics category, while the delegate theme is mainly represented in the psychology category.

The best represented WOS categories are mirrored in the number of articles in journals associated with these fields across D^3 themes. In particular, the top five journals (i.e., *International Journal of Social Robotics*, *Computers in Human Behavior*, *International Journal of Contemporary Hospitality Management*, *Frontiers in Psychology*, and *Interaction Studies*) accounted for 42% of all articles included in the final review. As an emerging research field in its nascent stage, it is not surprising that the remaining 112 articles appeared in 76 different journals, each of which has published five or fewer empirical studies on HRSI. Outlets related to consumer research in general included the *Journal of Business Research*, *Journal of Marketing Research*, *Journal of Service Management*, *Journal of Services Marketing*, and *Journal of Service Research*. The importance of studying consumer interactions with social robots in diverse research fields thus becomes evident, especially as robots take on increasingly complex social roles (e.g., receptionists, caretakers, teachers). That is, marketing/management journals are slowly entering the HRSI arena, but robotics, computer science, and psychology already offer some potentially valuable insights for studying social robots in service contexts.

	WOS Category Cluster	Total	Design	Delegate	Deploy
1	Robotics, Automation & Control Systems	63 (19%)	37	8	18
2	Psychology	55 (17%)	23	15	17
3	Hospitality, Leisure, Sport & Tourism	40 (12%)	25	11	4
4	Business & Management	39 (12%)	18	7	14
5	Healthcare Sciences; Medicine; Neuro-sciences	24 (7%)	16	6	2
6	Communication, Linguistics & Language	21 (6%)	10	2	9
7	Computer Science	20 (6%)	10	2	8
8	Education & Educational Research	18 (5%)	8	3	7
9	Engineering	10 (3%)	6	0	4
10	Geriatrics & Gerontology	10 (3%)	5	0	5
11	Ergonomics	8 (2%)	5	0	3
12	Information Science & Library Science	5 (2%)	2	0	3
13	Environmental Studies, Regional & Urban Planning	5 (2%)	3	1	1
14	Social Sciences, Sociology, Behavioral Science	4 (1%)	2	0	2
15	Chemistry, Physics, Materials Science	3 (1%)	0	0	3
16	Multidisciplinary Sciences	3 (1%)	1	0	2
17	Philosophy, Ethics, Art	2 (1%)	1	0	1

Note. One article can be allocated to up to three Web of Science (WOS) categories. Hence, the total count is higher than the total number of articles analyzed.

Table 3: Overview of WOS Categories

3.4.2.3 Methods and Sample Characteristics

Previous HRSI research features diverse methodological approaches. Table 4 lists the main methods applied, grouped as quantitative (e.g., field trials, lab or online experiments, surveys) or qualitative (case studies, interviews, focus groups). Most research relies on quantitative methods (88 % of studies analyzed), dominated by field studies, especially under the deploy theme, and online experiments under the design and delegate themes. In terms of sample characteristics, we found that most studies across D^3 themes included adult consumers. Others relied on vulnerable consumers (older adults, children; cf., Henkel et al., 2020) or university students.

3.4.2.4 Geography

The geographic patterns of research can indicate the generalizability of the results. Most empirical HRSI research across all D^3 themes has predominantly been conducted in Asia, Europe, and North and South America. While we found a smaller number of studies conducted in Oceania, none took place in African countries. Some results have been based on cross-continental (e.g., participants from the United States and Europe) and cross-country (e.g., participants from China and Taiwan) samples. The more frequently studied regions may have greater access to robots for empirical research. Research with real-life, embodied robots tends to be costly and resource intensive, and developed countries have greater access to financial resources to realize such studies. Furthermore, the greater need for introducing robots in services in these regions, due to demographic changes (United Nations, 2019) and nursing crises (Marć et al., 2019), might evoke more research attention. This latter explanation appears to be supported by the many articles linked to education, elderly care, and healthcare study contexts. Finally, many research facilities and researchers active in HRSI are located in these areas, which supports local data collection. Regardless of the reason, however, significant opportunities for global, cross-country research on HRSI clearly remain.

3.4.2.5 Study Contexts

Our analysis of extant HRSI literature reveals eight distinct study contexts in which consumer interactions with social robots are studied: (1) hospitality and tourism, (2) education, (3) elderly care, (4) healthcare, (5) domestic services, (6) public services, (7) retail, and (8) arts and entertainment. In addition, 14 studies related to multiple contexts. The distribution of study contexts across the D^3 themes was fairly similar. Notably, however, the domestic service context has predominantly been studied under the design theme, and we found a great majority of cross-context studies and a lack of studies in an elderly care context under the delegate theme. Zooming in, we found that, with the possible exception of retail, public services, and arts and entertainment, these contexts all represent highly interpersonal consumer service domains that require guidance from a service professional (Solomon et al., 1985). Such services are defined by frequent face-to-face interactions, close physical proximity, and low degrees of automation (National Center for O*Net Development, 2020b). They require intensive co-creative efforts by service providers and consumers to deliver value in the form of personal care, assistance, or emotional support (National Center for O*Net Development 2020a, 2020c, 2020d).

It is no coincidence that the contextual scope of our review is almost exclusively defined by services with a strong emphasis on interpersonal exchanges. From a service provider perspective, the interpersonal role cannot be easily replaced by technology, unlike service domains that rely less on interpersonal value creation, such as financial, consulting, or telecommunication services, which are hence not represented in our data set (De Keyser et al., 2019). Because the interactive element assumes such a central role in the domains under investigation, only an autonomous, embodied, and social technology that mimics the human service role as closely as possible (i.e., social robots) provides value-creating service to consumers. This factor helps explain the strong research interest in social robots in interpersonal service contexts; however, it cannot explain why other, arguably similar contexts have received little research attention (e.g., legal and insurance services, internal human resources).

3.4.2.6 Social Robot Types

To identify which social robot types have been studied, we extracted the names and morphologies (i.e., humanoid, machine-like, zoomorphic/cartoon/puppet-like, or android) of the robots used in each study. Table 4 lists the numbers of robots with different morphologies and common examples of such robot types. Across the D^3 themes, most of these robots take on humanoid appearances (65%), but others are machine-like (16%), zoomorphic, cartoon-, and puppet-like (13%), or android (6%). However, research under the deploy theme relied slightly more often on zoomorphic, cartoon-, and puppet-like rather than machine-like robots. This distribution may reflect the scope of our review because, for HSRI, humanoid robots might represent more natural sparring partners for consumers when compared with machine-like or zoomorphic robots. The latter might be specifically suitable for specific contexts, such as education and elderly care, where they have been heavily studied under the deploy theme.

We also limited our data set to mobile embodied social robots that exhibit human-like behavior. We excluded articles studying HRSI with only zoomorphic (e.g., *Paro*, a robotic pet seal; Baisch et al. 2017) or machine-like robots in industrial settings (e.g., Granulo et al., 2019), which do not exhibit human-like behavior in interactions with consumers. The few studies with android robots may reflect the limited availability of these robot types. Another explanation might rely on the uncanny valley theory (Mori et al., 2012), which predicts that androids evoke a high degree of eeriness that limits their suitability for service interactions with consumers (Mara & Appel, 2015). Overall, we identified over 70 different robots deployed in HRSI studies, including popular uses of the humanoid robots NAO (n = 62) and Pepper (n = 38), by the French company SoftBank Robotics, and different versions of the humanoid robot Robovie (n = 12), designed and produced by the Japanese company Vstone.

Dimension			**Total**	**Design**	**Delegate**	**Deploy**
Total No. of Articles			199	100 (50%)	32 (16%)	67 (34%)
Total No. of Studies			250	121	52	77
Method	*Quantitative*	*Field Study*	77	28	14	35
		Online Experiment	64	37	26	1
		Lab Experiment	47	32	9	6
		Survey	26	13	1	12
		Secondary Data	6	1		5
	Qualitative	*Interviews*	20	8	1	11
		Focus Groups	5	2	1	2
		Case Study	5			5
Sample Charac-teristics[a]	*Consumers*		144	70	28	46
	Vulnerable Consumers[b]		68	29	8	31
	University Students		50	26	18	6
Geography[c]	*Asia Pacific*		86	41	16	29
	Europe		64	32	23	9
	North/South America		62	32	6	24
	Oceania		16	9	2	5
	Cross-continental		13	6	3	4
	Cross-country			1		5
Study Context	*Hospitality & Tourism*		65	29	15	21
	Education		50	22	11	17
	Elderly Care		38	18	3	17
	Healthcare		37	14	10	13
	Domestic Services		21	20	1	
	Public Services		14	9	2	3
	Cross-context		14	4	10	
	Retail		8	3		5
	Arts & Entertainment		3	2		1
Robot Morpho-logy with Example Social Robots[a]	*Humanoid*	*NAO, Pepper, Ro-bovie*	207	98	37	72
	Machine-Like	*PeopleBot, Baxter, Care-O-bot 3*	52	32	5	15
	Zoomorphic/ Cartoon- & Puppet-Like	*iCat, Tega Patricc*	41	22	2	17
	Android	*Geminoid DK, HRP-4C, Repliee*	18	10	3	5

Note. Numbers reflect the number of studies.
[a] Numbers reflect the number of studies, but if one study considered different sample characteristics (e.g., university students and consumers) or used more than on robot (e.g., humanoid vs. machine-like) they were counted more than once. Thus, we systematically reviewed 199 articles, but the total counts refer to the number of studies.
[b] Vulnerable consumers include children and older adults (cf., Henkel et al., 2020).
[c] In three studies, no country was stated; no study conducted in Africa.

Table 4: Overview of Methods, Sample Characteristics, Geography, Study Contexts, Robot Morphologies, and Robots

3.4.2.7 Comprehensive Overview of Variables in HRSI Research

To gain a detailed overview of existing HRSI literature, we now present a comprehensive overview of variables studied based on our overarching D^3 framework as well as the affect–behavior–cognition (ABC) model (Breckler, 1984). For a synopsis of the variables, we consider service robot related antecedents, mediators, moderators, and individual consumer outcomes. For each variable type, we identify subthemes and patterns that can help integrate the dispersed findings (see Figure 8 for an overview).

D^3-related antecedents. We classified the independent variables in our data set as robot-related antecedents that clustered around the D^3 overarching themes. Design-related antecedents refer to different robot behaviors (e.g., displayed politeness, expression of social cues, degree of playfulness) and morphologies, antecedents related to the delegate theme pertain to different tasks and services delivered by a robot versus a human (e.g., teaching, performing clinical tests, service failure recovery), and deploy theme related antecedents encompass those where robots themselves depict the sole central focus in applied real-world settings (e.g., providing information to consumers in shopping malls or hotel lobbies).

Our analysis also revealed some studies capturing antecedents on individual consumer characteristics (e.g., gender, preexisting experience with robots) and situational factors (e.g., hotel segment, service organization information sharing). As such, they cannot be allocated to any of the robot-centered themes. However, while these studies help with understanding consumers' predispositions toward social robots in general, they reveal few insights into how to design, delegate, or deploy robots in consumer-facing services. Rather, they represent typical boundary conditions on when to design, delegate, or deploy service robots, also partly captured in the moderator studies. Due to their subordinate role, these variables are not depicted in Figure 8.

D³-RELATED ANTECEDENTS

DESIGN

[STUDIES FOCUSING ON ROBOT DESIGN ASPECTS]

Software (Behavior): Verbal and Nonverbal Communication: Expressing Emotions, Touch, Social Gestures (Gaze, Facial Expressions, Eye Contact, Forward-lean, Greeting, Polite Gestures), Privacy Protecting, Cultural Competence, Empathy, Friendliness, Politeness, Positive Language (Complimenting), Faulty Behavior, Helpfulness, Coolness, Interactivity, Autonomy, Motivational, Engaging, Laughing, Comforting, Playfulness, Entertaining, Self-disclosure, Friendliness, Authority, Adaptability, Level of Expertise, Personality, Intelligence, Mind-perception, Human-likeness, Social Presence, Trustworthiness, Learning Competency, Self-efficacy, Supportiveness, Emotional Engagement, Teaching Style, Utterance, Voice Type, Language, Service Failure Recovery, Introverted, Extroverted

Hardware (Appearance): Embodiment, Robot Morphology (e.g., Android, Humanoid, Zoomorphic, Machine-like), Robot Gender, Attire, Human-likeness

DELEGATE

[STUDIES FOCUSING ON DELEGATING HUMAN TASKS TO A ROBOT]

Human vs. Robot Delivering Different Services (e.g., Teaching, Clinical Tests, Rehabilitation, Serving, Kitchen Assistant, Reading Companion, Medical Assistance, Sightseeing, Public Service, Therapy), Human vs. Robot in Service Failure Situations / in Embarrassing Service Situations, Human Augmented or Substituted by Robot, Agency/Lying Perceptions of Human vs. Robot

DEPLOY

[STUDIES FOCUSING ON ROBOT DEPLOYMENT IN NATURALISTIC SETTINGS]

Robot exhibiting different behaviors or taking on services roles in the field (e.g., Shopping Mall, Retail Stores, Hotel Lobby, Museums, Therapy, Rehabilitation, Care Facilities): Active Communication, Relationship Forming, Emotion Expression, Giving of Meaning, Learning Companion, Collecting Medical Data, Social Assistance in Therapy, Serving, Guiding, Promotion, Entry Control, Long- vs. Short-Term Interaction, Classroom Environment: Studio vs. Interactive Laboratory, Robot Inside or Outside Store

MODERATORS

Robot-related: Aesthetics, Morphology (Human vs. Robot vs. Kiosk/Tablet), Human-likeness, Gender, Engagement, Sense of Humor, Service Failure Recovery Strategy

Human-related: Age, Gender, Personality Traits, (Preexisting) Attitude towards Service Robots, Emotional Stability, Interaction Comfort, Familiarity w. Robot, Differences In Learning, Knowledge Status, Learning Difficulty, Openness to Change, Preference for Ethics, Responsible Business, Customers Attributions (Service Enhancement, Cost Reduction), Use Experience, Personal COVID-19 Condition, Need for Human Interaction, Anxious Attachment Style, Personality Type

Situation-related: Task Similarity/Difficulty, Hotel Segment, Interaction Time/Quality, Group Size, Pandemic Situation, Human Staff Present, Service Failure Type, Industry Context

MEDIATORS

Robot-related:
Robot Human-likeness, Social Presence, Anthropomorphism, Mind Perception, Perceived Credibility/Sincerity, Ability, Eeriness, Performance Expectancy, Satisfaction w. Robot, Warmth, Competence

Human-related:
Enjoyment in Interaction, Perceived Benefit, Consumer Innovativeness, Identity Threat, Perceived Robot Innovativeness, Perceived Ethical and Societal Reputation, Control, Value Perception, Attitude, Effort Expectancy, Positive Emotions, Acceptance, Usefulness, Trust, Emotional Appeal, Psychological Risk, Ambiguity, Pleasure

INDIVIDUAL CONSUMER OUTCOMES

AFFECT

- Physical Response: Physical Stress, Pain, Galvanic Skin Response, Blood Pressure, Heart Rate, Proximity to Robot
- Verbal Response: Affective States, Emotional Response, Enthusiasm, Connectedness, Enjoyment, Surprise, Amazement, Confidence, Well-being, Feeling of Co-presence, Fear of Job Loss, Intrinsic Motivation, Affective Trust, Fear, Pain, Anxiety, Discomfort

BEHAVIOR

- Social/Interaction Behavior (e.g., Sending Social Cues, Talking to Robot, Laughing, Smiling), Taking Robot Advice, Self-disclosure, Social Conformity, Compliance, Abusive Behavior, Engagement, Proximity to the Robot, Social Distance, Hesitation
- Learning, Retention of Messages, Intention to Stay in Hotel, Task/Test Performance, Compensatory Behavior, Taking Additional Medicine
- (Intention to/of) Use/Future Interaction, Brand Usage Intent, Word of Mouth, Willingness to Pay

COGNITION

- General Perception of Robot Service: Usefulness, Robot Task Performance, Satisfaction, Acceptance, User Expectations, Use Cases, Novelty, Service Experience/Quality, Brand Experience, Positive/Negative Attitudes, Value Added, Responsibility Attribution, Blame for Lying, Anticipated Embarrassment, Loyalty
- Related to Robot Appearance: Aesthetics, Physical Attraction, Anthropomorphism, Texture, Physical Presence, Immediacy
- Related to Robot Behavior:
  - Preferences for Verbal (e.g., Speech Rate) and Nonverbal Behavior (e.g., Social Cues, Gaze), Perfect Automation Schema
  - Social Presence, Human-likeness, Mind Attribution, Animacy, Intelligence, Social Skills, Agency Ascription, Autonomy, Adaptability, Sociability, Rapport Building Capabilities, Helping Behavior
  - Sympathy, Politeness, Likeability, Warmth, Competence, Perceived Personality, Responsibility Attribution, Trust, Empathy, Deceiving Intent
  - Perceived Safety, Capability, Consumer Self-efficacy and Relations when Interacting with Robot, Privacy Concern, Sharing Personal Information

Note. This comprehensive overview pictures all variables by indicating the terminology used in the respective study. Hence, while variables such as anthropomorphism and robot human-likeness, in essence, can be regarded as identical constructs, their definition may differ from article to article. Further, some constructs appear in more than one variable category (i.e., antecedents, moderators, mediators, outcomes) as they have been adopted in different ways in the underlying research models of the various studies analyzed.

Figure 8: Overview of Focal Variables Studied

Individual consumer outcomes. Reflecting the variation in disciplines, the literature on HRSI has focused on a wide variety of individual consumer psychological and behavioral reactions to the design, delegation, and deployment of service robots. Our analysis of these outcome variables revealed that they map on the ABC model (Breckler, 1984). This tripartite model of human responses to environmental stimuli has been widely adopted to explain the components that reflect inter-individual attitudes (Haddock & Maio, 2019), consumer engagement (Brodie et al., 2011), consumer-related consequences of flow in computer-mediated environments (Valinatajbahnamiri & Siahtiri, 2021), and consumer brand engagement (Hollebeek & Macky, 2019). In our review, the stimuli represent consumers' exposure to social robots in studies under one of the three overarching themes of design, delegate, or deploy. The variety of consumer reactions, in turn, can be clustered as affective, behavioral, or cognitive outcomes. Affect refers to "an emotional response, a gut reaction, or sympathetic nervous activity" (Breckler, 1984, p. 1191). It can be measured by monitoring physiological responses (e.g., blood pressure) or collecting verbal or written reports of feelings or mood. Behavior reflects exercised actions or verbally expressed behavioral intentions (Breckler, 1984), which can then be measured through observations in (field) experiments or approximated in surveys of behavioral intentions. Finally, the cognitive component comprises beliefs, knowledge structures, perceptual responses, and thoughts; these measures require verbal or written statements from participants (Breckler, 1984).

As suggested by Breckler (1984), we further partitioned affective reactions into physical responses (e.g., blood pressure, heart rate) and verbal reports of emotional states (e.g., enjoyment, fear) expressed by consumers when they interact with an embodied social robot. Studies with a behavioral focus mostly related to the exhibited social behavior of the robot's interaction partner (e.g., displaying social cues, engagement with robots), context-specific service outcomes (e.g., learning, test performance), or usage intentions. Cognitive outcomes can be partitioned into three subcategories of consumer perceptions of general robot service provision (e.g., usefulness, attitudes toward robot), robot appearance (e.g., perceived aesthetic, physical attractiveness), and robot behavior (e.g., speech and gaze behavior, human-likeness).

Finally, a few studies have also assessed consumer outcomes on a global rather than individual level. Findings usually addressed both the barriers and facilitating conditions of designing, delegating, and deploying social robots (e.g., technical issues, robot capabilities) with others. They also focused on general and specific use cases for social robots in different consumer-facing service settings. Because such global outcomes only play a minor role in the HRSI literature, they are not depicted in Figure 8.

Mediators and moderators. In our data set, 60 articles reported on how (29) and when (31) designing, delegating, and deploying social robots in service leads to different consumer outcomes. Resulting from our bottom-up analysis, we clustered these mediators and moderators into robot-, human-, and situation-related variables. Robot-related mediators refer to processes centered around the robot, including its perceived human-likeness or social presence; human-related mediators take the perspective of a robot's interaction partner, such as perceived enjoyment or human identity threat. Similarly, the moderators may be robot-related (e.g., aesthetics, morphology), human-related (e.g., age, gender, personality traits, preexisting attitudes toward social robots, interaction comfort, familiarity with a robot), or situation-related (e.g., task difficulty, group size). Some studies include human-related, context-specific moderators as well, such as students' learning difficulties in an education context.

3.5 Key Insights and Implications along the D³ Framework

We next zoom in to discuss key insights related to consumer preferences when interacting with embodied social robots according to the three themes of our newly developed D³ framework (i.e., design, delegate, deploy) and derive practical implications therefrom. In Appendix E, we provide the basis of this analysis in tables presenting specific information about study designs of each included article in our final data set (i.e., antecedents, robots deployed, ABC model outcome variables) and key findings, first by each D³ theme and second by study context.

3.5.1 Key Insights from Design Theme

Studies about the software designs for social robots in different service contexts mainly aimed to understand the effects on consumer outcomes of either the robot's behavior or its appearance to identify consumers' preferences.

3.5.1.1 Behavior

Depending on social robots' human-like communication behavior (e.g., politeness, benevolence, voice pitch; Lyons et al., 2021. Lee et al., 2017; Zhu & Kaber,

2012) and the message content (i.e., self-disclosure; Johanson et al., 2019) consumers engage more with the robots and find them less intimidating and more trustworthy (Lyons et al., 2021). If the robot's human-like behavior evokes perceived intelligence and human-likeness in consumers, it contributes to building consumer rapport and hospitality experiences (Qiu et al., 2020). In terms of language style, research has found that using a native (vs. non-native) accent evokes more positive emotions among consumers toward social robots in a healthcare context (Tamagawa et al., 2011). Furthermore, consumers prefer social robots speaking in a literal, direct language, and at a moderate pace (Choi et al., 2019a; Pan et al., 2015; Shimada & Kanda 2012). The presence of nonverbal behavioral patterns (e.g., gestures, gaze, changing eye color) encourages consumer interactions with social robots (van Pinxteren et al., 2019a) and consumer perceptions of hedonic values (e.g., Johnson et al., 2016).

Research shows that when robots act according to the consumer's expectations for a certain task, the interaction outcomes are more positive. For example, findings indicate that if a robot's programmed personality and demeanor are customized to the task at hand, it promotes consumers' perception of the robot's social attractiveness and limits perceived eeriness (e.g., Sundar et al., 2017). Another example in a healthcare context shows that a robot's patient-centered (vs. task-centered) behavior also positively affects perceived emotional intelligence (Chita-Tegmark et al., 2019). Moreover, when robot behaviors signal personalization, the provision of service to consumers is more successful. For example, personalized behavior improves learning outcomes for children (e.g., Baxter et al., 2017).

3.5.1.2 Appearance

Studies that focused on hardware design suggest that consumers prefer humanoid social robots over zoomorphic and machine-like robots (e.g., Belanche, Casaló, Flavián, & Schepers, 2020; Chu et al., 2019; Tu et al., 2020; Walters et al., 2008). A potential explanation for this preference might be that an embodied, humanoid robot increases consumers' mind perceptions and positive personality attributions (e.g., Broadbent et al., 2013). Moreover, different robot morphologies (humanoid, zoomorphic, machine-like) also seem to evoke different cognitive processes and behaviors in consumers. Specifically, humanoid and machine-like robots are perceived as credible, and humanoid and zoomorphic robots are more easily adopted as companions by children in education services (Broadbent et al., 2018; Edwards et al., 2016).

Although general studies reported a positive effect of human-like appearances (e.g., Belanche et al., 2020; Walters et al., 2008), other studies found that in certain roles in services, other morphologies are preferred. For example, a caricatured robot appeared to be preferred over a humanoid one when robots took on concierge roles (Shin & Jeong, 2020). Furthermore, machine-like robots seem better suited for executing security tasks than humanoid or zoomorphic robots (Li et al., 2010), and small robots are more effective in promotional tasks than human-sized ones (Shiomi et al., 2013), while human-sized robots are preferred in guidance tasks (Kanda et al., 2008). We also noted evidence of the positive effects of gender-stereotypical occupational role matching (i.e., male robots for domestic security and female robots for domestic care; e.g., Kuchenbrandt et al., 2014) in terms of robot hardware design.

As outlined above, morphology has a strong impact on consumer interactions with social robots in services. However, research also finds that individual consumer differences (i.e., general trust in technologies, affinity for the robot) might mitigate the effects of morphology on, for example, adoption intentions (e.g., Belanche et al., 2020; Tussyadiah et al., 2020).

3.5.1.3 Summary of Implications from Design Theme

Across the results clustered under the design theme, we derived concrete implications for robotic software (i.e., behavior) and hardware (i.e., appearance) design to match consumer preferences around three subthemes: (1) human-like verbal and nonverbal behavior, (2) task-related/personalized behavior, and (3) appearance. First, research conducted in various services suggests that robots should be designed to actively engage with consumers, encourage interaction, show empathy, be sociable, and exhibit emotional relationship-building capacities. Ideally, they should exhibit a range of nonverbal, human-like behaviors (e.g., gaze, social gestures) to foster interaction comfort. Furthermore, the designs should ensure robots act politely and in a consumer-centered manner.

Second, robots should be able to provide personalized services, adapted to individual preferences (e.g., speech pace) or learning stages. A robot’s personality, demeanor, and gender design should fit the task at hand. However, executives are advised to be cautious with respect to the wider context of gender and stereotype effects. Robots should also be able to explain their own, task-related use to individual users.

Third, we derived implications for a robot's hardware design, but caution executives to recognize the mixed results regarding human-like appearances. In most cases, humanoid robots are preferred to machine-like or zoomorphic robots, but prior research has also revealed individual differences in these preferences in different services (e.g., hospitality and domestic services). For example, in hospitality contexts, executives should acknowledge the varying expectations of guests in diverse hotel segments. Task delegation to a machine-like service robot could be viable for budget hotels; in premium segments, however, consumer-facing tasks should be delegated to humanoid robots (Chan & Tung, 2019). Moreover, morphology preferences in terms of the robot's height seem task-dependent. With guidance tasks, for example, users want human-sized robots, but small robots are preferable for conducting promotional activities in a retail context. Androids can evoke feelings of eeriness and high user expectations that current state-of-the-art technology cannot yet attain for most service tasks (Mori et al., 2012). Thus, at the current stage of robot development, it does not seem advisable to equip social robots with android hardware for consumer-facing services.

3.5.1.4 Overall Evaluation of the Contribution and Gaps in Knowledge associated with the Design Theme

Studies under the design theme contribute to the literature by shedding light on the effects on consumers of robots' different behavior and/or appearance in internal and external service encounters. Although most of the studies in our data set fell under the design theme and research has created a solid knowledge base, some gaps remain. While prior research has predominantly relied on lab, online, and field experiments with adult consumers in Asia, Europe, and North America having interactions with humanoid social robots, longitudinal designs are underutilized, as are studies of consumer interactions with robots in cross-regional settings and with different consumer types. Moreover, investigations to date of the effects of non-humanoid robot morphologies and some service contexts, such as retail or arts and entertainment, have been neglected by research under the design theme. Apart from research opportunities related to the study settings, we also identified additional avenues for research based on our analysis of the key findings pertaining to (1) consumer preferences and (2) consumer–robot collaboration. We discuss these research avenues in detail in Section 3.6.

3.5.2 Key Insights from Delegate Theme

Delegate studies, in which human employees and social robots are directly compared in providing services, show that robot performance matches or even exceeds human employees' performance (e.g., in terms of teaching outcomes and students' learning performance, kitchen assistance, or taking medical tests; Desideri et al., 2019; Mann et al., 2015; Thellman et al., 2017; Wu et al., 2015; Yueh et al., 2020). Moreover, Broadbent et al. (2010) showed that blood pressure levels do not differ in response to a robot or human nurse, so there is no evidence that social robots cause extra stress, even in highly personal services.

However, depending on the context and task, we also found that robots are not preferred over human employees. On the one hand, delegating assistive living tasks such as domestic chores (e.g., shopping, garbage disposal, delivering food; Smarr et al., 2014) or troublesome tasks (e.g., dealing with complaints, picking lost items out of the trash; Hayashi et al., 2012) to robots is positively perceived, and robotic service providers are preferred over humans in potentially embarrassing service encounters (Pitardi et al., 2022). On the other hand, humans are perceived as irreplaceable when it comes to socially assistive and interactive services such as personal care and leisure tasks (Smarr et al., 2014). Moreover, in hospitality contexts, the interaction quality that guests perceive is better when they interact with human service providers rather than robotic ones (Choi et al., 2019). These effects might be due to the different attributions humans and social robots evoke in consumers. As Čaić et al. (2020) showed, consumers attribute slightly less competence and warmth to robot coaches than to humans, which influences consumers' behavioral intentions related to physical activity.

As another cautionary finding related to task delegation to social robots in services, Mende et al. (2019) revealed perceptions of greater eeriness and identity threats in response to robots versus human staff, which can cause consumers to engage in status consumption or choose unhealthy options. Additionally, substituting for human staff can also damage the service organization's ethical and societal reputation in the eyes of consumers (McLeay et al., 2021). Finally, Rainear et al. (2019) found that risk message retention is lower if the message is delivered by a robot rather than a human. Consumers seem to ruminate on visual stimuli and the content delivery medium rather than the content and behavior during message delivery, such that the robot functioned as a technological distractor.

3.5.2.1 Summary of Implications from Delegate Theme

From research directly comparing humans with robots delivering services, we can derive implications regarding the effectiveness of human versus robot service provision and which tasks are accepted by consumers to be delegated from humans to social robots. Research suggests that various tasks can be successfully delegated to embodied social robots, including teaching, reading, assistive healthcare, household chores, kitchen assistance, and room service. Consumers also accept the delegation to robots of unpleasant tasks (e.g., trash picking, dealing with complaints), domestic chores (e.g., shopping, garbage disposal), and tasks in information management (e.g., emergency alerts). Further, delegating tasks in highly personal service encounters (e.g., elderly care) or potentially embarrassing ones (e.g., buying hemorrhoid crème) from humans to robots is well accepted and perceived as useful. However, tasks related to personal care and leisure should not rely solely on social robots. Moreover, robots can create technological distractions, so they should be used for risk messaging only very carefully.

3.5.2.2 Overall Evaluation of the Contribution and Gaps in Knowledge associated with the Delegate Theme

Studies under the delegate theme contribute to the literature by directly comparing human service providers to embodied social robots. The results provide implications on what tasks and under which circumstances they should be delegated from humans to robots. Based on our review, the fewest analyzed studies fall under the delegate theme, which opens up avenues for future research. Prior research has predominantly relied on quantitative approaches using online and field experiments. Additionally, a great proportion of studies were conducted with university students interacting with humanoid social robots. Those studies mostly took place in Asia or Europe. Moreover, most studies thus far have been conducted in hospitality and education service contexts. Hence, opportunities for novel insights remain in using more qualitative methods and in quantitative methods apart from online and field experiments. Further, it would be valuable to study consumer interactions with robots in thus far neglected service contexts and with vulnerable consumers. This latter aspect is specifically relevant for ethical considerations when delegating service tasks from humans to social robots. Based on our analysis of key findings under the delegate theme, we identified two additional clusters for future research in relation to (1) consumer preferences and (2) situational factors in task delegation, which we discuss in Section 3.6.

3.5.3 Key Insights from Deploy Theme

Findings under this theme suggest whether, when, and how social robots should be deployed in services by studying consumer interactions with social robots in real-world settings.

Research shows that robots can be successfully introduced in different real-world consumer service settings. For example, when introducing a robot in a classroom, both teachers and students generally accept and adopt it and exhibit relationship-building behaviors (e.g., Michaelis & Mutlu, 2018). Moreover, field experiments with assistive robots, such as the Personal Robot (PR2) and Domestic Robot (DoRo), show that older consumers accept robots that help them with household chores in their own home (e.g., Di Nuovo et al., 2018). In hospitality contexts, consumers readily accept robots and routinely seek interaction opportunities with them (Tung & Au, 2018). Furthermore, introducing social robots in healthcare contexts can enhance the efficiency of service provision (e.g., rehabilitation, medical coaching, exercising, medical recording). For young patients, social robots improve their engagement, independence (Butchart et al., 2019), and communication abilities during rehabilitation (Pulido et al., 2017). Adult patients also report more positive perceptions of social robots after (vs. before) actual interaction (Casas et al., 2019; Winkle et al., 2020). In shopping malls, social robots evoke curiosity and approach tendencies among children but abusive demeanors as well (Nomura et al., 2016; Sabelli & Kanda, 2016).

We found mixed results in terms of longitudinal effects. On the one hand, attitudes toward social robots tend to improve with time and interaction frequency (Stafford et al., 2014), which might explain why early studies yielded more negative attitudes and comparatively low intentions to use robots (e.g., Wu et al., 2014), but more recent studies signal greater perceived usefulness and attractiveness (Melkas et al., 2020). On the other hand, research indicates that consumers might interact less with a social robot once the novelty effect vanishes. For example, Kanda et al. (2007) found that two-thirds of students become bored with and consequently reject social robots over time.

Studies under the deploy theme further highlight that consumers display avoidance-related tendencies toward robots if not actively engaged with them or if they are not located in an easily accessible area (Pinillos et al., 2016; Rodriguez-Lizundia et al., 2015). Moreover, consumer value perceptions of robots in various consumer-facing services seem deeply rooted in their individual acceptance of technology (i.e., perceived usefulness, ease of use, innovativeness) and service quality perceptions (e.g., personal engagement, tangibles; de Kervenoael et al., 2020; Cha, 2020).

3.5.3.1 Summary of Implications from Deploy Theme

Our implications from the deploy theme are structured along two dimensions: (1) whether and when and (2) how to deploy social robots in services. Concerning the former, managers should consider the nature of the task when deploying robots. Preference should be given to assistive rather than social tasks. Educational organizations might anticipate mixed results in terms of learning outcomes and might be advised to refrain from deploying robots in higher education settings, at least with current state-of-the-art technologies. In terms of how, managers should familiarize consumers with robotic technology to overcome adoption barriers. Furthermore, robots should be placed in quiet, accessible areas in real-world contexts (e.g., hotel lobbies, train stations), and they should remain in an awake mode to foster interactions. In public, strict interaction rules should be imposed, especially for children. Potential users should be clearly informed about diverse robot use cases and receive information about the affordability and entertaining value of robotic services. Further, it is advised to program robots to be able to explain their own uses when deployed in real-world consumer settings.

3.5.3.2 Overall Evaluation of the Contribution and Gaps in Knowledge associated with the Deploy Theme

Studies under the deploy theme contribute to literature by studying consumer interactions with embodied social robots in naturalistic service settings. In so doing, research under this theme creates an understanding of when, where, and for which target groups social robots can be effectively deployed in consumer-facing service contexts. Against the background of the theme, it was to be expected that the majority of prior research relied on field experiments and interviews. Nevertheless, virtual reality technology could be an alternative for studying consumer interactions with social robots in naturalistic settings in the future. The majority of research has been conducted in Asia and North America with humanoid social robots; thus, gaps remain related to the deployment of other social robot types in other regions, which could shed light on intercultural differences and similarities when deploying social robots. Based on our analysis of key findings under the deploy theme, we identified three additional clusters for future research avenues relating to (1) consumer preferences, (2) consumer outcomes and mechanisms that explain the effects of robot deployment in naturalistic service settings, and (3) environmental factors to be considered. We discuss these areas for future research in detail in the next section.

3.6 Future Research Agenda

Although our synthesis of extant HRSI research provides concrete insights into consumer preferences when interacting with embodied social robots, along with implications for successful integration of these robots in consumer–firm interactions, critical questions remain unaddressed. Thus, in direct response to our third research question, we pinpointed crucial research needs for future studies of consumer interactions with social robots in services. We first propose future research needs identified through our analyses related to methods and samples deployed, geographic regions, robot types, and study contexts, as well as focal variables across the D^3 themes. Then, we present future research avenues delineated from our analysis of the key findings of each theme of the framework, as detailed in Table 5.

3.6.1 Future Research Needs according to Methods, Sample Characteristics, Geography, Study Contexts, Social Robot Types, and Focal Variables

3.6.1.1 Methods and Sample Characteristics

Although our review reveals a great diversity in methodological approaches, longitudinal studies are still scarce. In light of reported habituation effects (e.g., Brandl et al., 2016), we urge researchers to conduct more longitudinal studies. Due to diverse validity demands across disciplines and challenging study conditions using social robots, studies with clear manipulations of robot behavior and appearance factors in controlled environments are scarce. We thus recommend that researchers address these internal validity concerns in future study designs. Noting the samples in the current, cross-context HRSI research, we also found many studies with relatively small sample sizes (e.g., Torta et al., 2014), which are potentially underpowered and hamper generalizations to the population in general. We thus urge researchers to gather larger samples when designing new and replicating previous studies. We also recommend scholars include understudied consumer groups. For example, adolescents have great purchasing power in retail stores (Olick, 2019), where social robots are increasingly adopted; however, their needs with regard to interactions with such robots differ from those of other consumer groups (Björling et al., 2020).

3.6.1.2 Geography

In our data set, we found no studies conducted in Africa and only a handful in South America. Yet these regions host many consumers at the base of the pyramid, with specific needs and tremendous transformative potential for service robots (Fisk et al., 2016). We encourage researchers who study consumer interactions with social robots in these regions to acknowledge the potential cultural and structural differences in robot perceptions and consumer preferences. Furthermore, we advise scholars to conduct cross-regional studies to identify potential cultural influences. As social robots are integrated into consumers' daily lives, governments might need to enforce new regulations (Leenes et al., 2017). However, these might differ from region to region and might affect each of the D^3 themes differently. For example, in some countries, the deployment of social robots in care facilities (delegate; deploy) might be forbidden, while in other countries, android robots (design) might be prohibited due to ethical concerns. We urge researchers to investigate the influence of governmental regulations in the context of HRSI.

Study contexts. In our data set, eight distinct study contexts are represented, with a strong research focus on hospitality and tourism, education, and elderly care. However, some highly interpersonal service domains where social robots might be effectively deployed for service delivery (e.g., legal and insurance services, internal human resources) have received relatively little research attention, meaning that context-specific effects on HRSI pertain to only a subsection of contexts identified in prior studies. Continued research should pay particular attention to less investigated domains to expand the broader comparative framework and derive implications for the successful adoption of social robots in all contexts where such robots might potentially interact with consumers.

3.6.1.3 Social Robot Types

We note a strong focus in the literature on humanoid robots, especially NAO and Pepper. We encourage future research to validate results and expand knowledge by using different humanoid and non-humanoid robot types that exhibit human-like behavior, as they have proved to be effective sparring partners in some service contexts (e.g., Chan & Tung, 2019; Kory Westlund et al., 2017).

3.6.1.4 Focal Variables

The synopsis of variables studied in previous research reveals substantial numbers of studies devoted to robot design-related antecedents. Furthermore, despite including outcomes reflecting all ABC model components, we note that relative to cognitive consequences, the affective and behavioral outcomes are underrepresented, despite their central role for interaction success (Brodie et al., 2011). A particularly promising avenue thus lies in studying antecedents related to the delegate and deploy themes and the behavioral and affective reactions of service agents. Prior calls for research noted the need for studies on the impact of robots on marketing-related outcomes (e.g., service quality, loyalty; Wirtz et al., 2018), but such studies still remain a rarity. We encourage scholars to study these relationships to help clarify when and how to adopt social robots in services. In addition, even though studies including moderators and mediators have increased significantly in the last two years, less than 30% of the studies in our data set considered underlying mechanisms and boundary conditions of consumer outcomes. We thus recommend scholars include these variable types in their research designs.

3.6.2 Future Research Needs according to the D^3 Framework Themes

Based on the analysis of key findings according to each D^3 framework theme, we developed concrete research questions that address critical future needs for consumer research, which we depict in Table 5. We further cluster these questions for each D^3 theme according to the intended study focus.

For all three themes (i.e., design, delegate, deploy), we develop concrete future research questions related to a focus on *consumer preferences*. These future research needs all address consumer preferences with regard to various aspects of robot design (hardware and software), the delegation of certain tasks to robots, or preferences regarding the deployment of social robots in real-world service settings. For example, under the design theme, we identify research needs regarding which specific robot characteristics (hardware and software) mitigate consumers' anxiety and foster trust and relationship-building behavior. Under the delegate theme, we offer open questions regarding what task types robots should never meddle in, considering consumer preferences, along with potential security risks and ethical issues, and we identify research gaps related to vulnerable consumers (i.e., the elderly and children). Finally, research avenues related to consumer preferences under the deploy theme include the investigation of how robots should be introduced to consumers and what interaction rules are accepted by consumers and are thus effective when deploying robots in different settings, such as in public.

Under the design theme, we additionally identify research needs related to the study focus of *robot–consumer collaboration*. Service provision is not a one-way street and depends on consumers' willingness to collaborate with a service provider (Vargo et al., 2008). Hence, we encourage scholars to investigate what verbal and nonverbal behaviors as well as what type of robot morphology encourage consumers to collaborate with social robots in service provision.

Under the delegate theme, we identified additional research gaps related to *situational factors*. For example, we know from cross-sectional studies that human staff are preferred over robots in certain settings, such as personal assistance tasks. However, this might be due to a novelty effect. Future research might investigate whether a habituation effect sets in and consumers' initial assessment with regard to the delegation of tasks related to personal care might change over time. Moreover, future research could investigate how the current COVID-19 pandemic might foster the acceptance of social robots and decrease ethical concerns related to the delegation of tasks to robots on behalf of human staff in different services.

Finally, under the deploy theme, we identify open questions related to two study foci: (1) *consumer outcomes and mechanisms* and (2) *environmental factors*. The former includes questions regarding the long-term effects of robot deployment, such as consumer well-being, the change of consumer trust during extended usage periods, and psychological mechanisms of consumer behavior during and after the deployment of social robots. The latter includes open questions related to how business environments need to be designed to ensure a successful deployment of social robots, as well as how social robots can be effectively deployed in special service environments (e.g., in luxury services).

DESIGN	DELEGATE	DEPLOY
Consumer preferences ▪ Which robot characteristics (behavior and appearance) mitigate anxiety in interactions with robots? ▪ How can robot hardware and software design foster trust and diminish privacy threats in consumers in different service contexts? How should these aspects be adapted for different cultures? ▪ How should social robots use humor to evoke positive consumer outcomes and decrease stress and anxiety levels of consumers (e.g., in healthcare services)? ▪ How should robot language and accent be adapted to the consumers' local culture? What are the potential threats for using specific accents in multicultural settings? ▪ How should the interaction behavior of machine-like social robots be designed to evoke trust and engagement in consumers? ▪ How should robotic hardware and software be designed to speak to both male and female consumers in different service contexts? ▪ What are morphological and material characteristics of existing robot models that decrease consumers' contamination concerns during the pandemic and beyond? **Robot–consumer collaboration** ▪ What human-like verbal and nonverbal behaviors specifically drive consumer engagement and relationship building in different consumer service contexts? ▪ How can consumer collaboration with social robots be improved through robot behavior and appearance design?	**Consumer preferences** ▪ What type of tasks can be effectively delegated to social robots to promote sales and consumer experiences? ▪ Are there any (and which) tasks that robots should never meddle in, such as elderly care or other personal contexts? For example, should a robot autonomously manage access control to private homes? What are potential security risks and ethical considerations? ▪ Which services should be delegated to a robot interacting with vulnerable consumers? How will intensive task delegation to robots affect children's development and the elderly's maintenance of independence? ▪ Why do robot-staffed hotels fail? What is an optimal human–robot ratio considering consumer preferences? **Situational factors** ▪ From extant cross-sectional studies, we know that older consumers prefer humans over robotic assistance. Could this be due to the novelty effect? Would longitudinal studies confirm these results, or would a habituation effect set in? ▪ How can tasks in emotionally charged situations be effectively delegated to social robots? ▪ Does the COVID-19 pandemic support faster adoption of social robots (e.g., in healthcare contexts) and decrease ethical concerns related to delegation of tasks to robots on behalf of human staff?	**Consumer preferences** ▪ How should robots be introduced to consumers? What information is most relevant for subsequent acceptance and use? ▪ How should robots be marketed to consumers and introduced to staff for a successful deployment? ▪ Which interaction rules for consumers (e.g., children) when interacting with robots in public services contexts are effective at promoting engagement, yet decrease the risk of abuse? **Consumer outcomes and mechanisms** ▪ What are the long-term effects of engaging with socially assistive or interactive robots on the psychological well-being of consumers (e.g., in elderly care or education services)? ▪ How do consumers' trust and commitment toward social robots change over time (e.g., in domestic care or elderly care contexts)? ▪ What are the psychological mechanisms that drive consumer behavior (e.g., discrete emotional elicitation, engaging with robots) during and after the deployment of social robots? **Environmental factors** ▪ How do business environments need to be designed to successfully deploy social robots? ▪ How can robots be successfully deployed in special service environments such as luxury service contexts?

Table 5: Future Research Agenda according to the D^3 Framework Themes

3.7 Discussion

This systematic review aimed to integrate empirical findings from research addressing consumer service interactions with embodied social robots (i.e., HRSI) across scientific fields to provide academics a comprehensive assessment of existing knowledge, as well as to give managers insights into how to effectively introduce consumer-facing robots. To this end, we make four key contributions.

First, our comprehensive review of more than 13,500 articles represents the first systematic, integrative analysis of empirical HRSI studies across scientific fields focusing on a clearly defined robot type to inform the suitability of such robots for consumer-facing services. This holistic approach, paired with our detailed descriptive analyses, establishes a thorough overview of existing knowledge beyond the boundaries of the business literature.

Second, to structure the vast amount of extant HRSI literature, we developed a novel tripartite D^3 framework. As we showed, this framework can be deployed to derive detailed insights into consumer outcomes when interacting with social robots, and it also provides concrete implications for ensuring the successful integration of social robots in services. Our study thus directly responds to previous calls for assessing the roles and impact of social robots in service provision (Lu et al., 2020). This framework can further serve to structure and design future consumer research or to define strategies for including social robots in different services.

Third, based on our analysis of the consumer outcomes studied in extant research, we noted parallels with the ABC model advanced in social psychology. Employing this model in HRSI research offers an intuitive structure of the focal variables studied. Applying this lens in conjunction with a morphological classification of social robot types on a study's context-specific level yields a detailed overview of key insights per D^3 theme, as depicted in Appendix E and F. Our work may thus serve as a comprehensive directory for researchers interested in understanding which variables have been studied in HRSI.

Fourth, practitioners still struggle to effectively integrate social robots in consumer-facing services (e.g., Shead, 2019). Our overarching D^3 framework of HRSI and its implications provide an initial guide to the pitfalls and opportunities associated with embodied social robots providing various services to consumers. However, critical questions remain unaddressed. From our review, we pinpointed research needs and formulated concrete research questions (Table 5). We thus contribute to the literature by providing new impetus for future research activities.

Although we executed our literature review with the highest level of diligence, we acknowledge some limitations of our approach. First, we do not claim to capture the entirety of research articles published on this topic. Rather, we bridged the impediment of the extensiveness of empirical evidence on HRSI across disciplines by restricting our sample to articles published in journals with specific quality standards. Second, in our data collection, we did not preregister our review and relied on one search database, which stands in conflict with PRISMA (Page et al., 2021). Although the WOS database includes the main corpus of research in diverse scientific fields published in scholarly qualified peer-reviewed journals (Antons & Breidbach, 2018), we acknowledge that other databases and less strict quality criteria might have flagged additional papers. Third, in scope with our review focus, we only included articles that investigated HRI in consumer-facing service contexts. Future reviews may integrate findings from research outside such settings (e.g., studies that investigate human behavior when playing strategic games with social robots; Cominelli et al., 2021). Fourth, even though we analyzed the literature based on several dimensions, we neglected a detailed analysis of theoretical foundations. This is partly due to the transdisciplinary nature of our review, because the identification of theoretical bases of studies in fields other than marketing, management, and psychology is not always straightforward. Still, future reviews may integrate this dimension. Fifth, our inclusion criteria specified a time span of published articles from the early 1970s onward. While sophisticated Wizard of Oz experiments were theoretically possible to conduct in an earlier time frame with respective social robot prototypes, we found that no articles published before 2007 fit the scope of our review. Future reviews should consider the technological advancements and specify the inclusion criteria related to the time span of published articles accordingly. Finally, we structured the literature under the design, delegate, and deploy themes according to the prevailing study focus. This approach harbors an interpretive element, and other coders may partly disagree with the D^3 theme we allocated to ambiguous articles (i.e., those combining more than one theme).

3.8 Conclusion

This review contributes to literature by providing scholars and practitioners with a comprehensive and structured overview of the great wealth of research from different scientific fields on consumer interactions with embodied social robots in service settings and identifies relevant gaps in the literature. Considering the growing market value of and interest in embodied social robots in consumer interactions and the increased relevance of robotic services provided by such robots, especially during the COVID-19 pandemic (Finsterwalder & Kuppelwieser, 2020), our review provides a comprehensive synthesis and a structuring framework of the extant HRSI literature, helping business managers make informed decisions on whether, when, and how to deploy social robots in consumer-facing services. It also gives researchers a sense of the status quo of research on HRSI and provides a basis for complementing our knowledge of how to effectively deploy social robots in service.

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4. Robotic Transformative Service Research: Deploying Social Robots for Consumer Well-Being During COVID-19 and Beyond[6]

Abstract

Besides the direct physical health consequences, through social isolation COVID-19 affects a considerably larger share of consumers with deleterious effects for their psychological well-being. Two vulnerable consumer groups are particularly affected: older adults and children. The purpose of the underlying paper is to take a transformative research perspective on how social robots can be deployed for advancing the well-being of these vulnerable consumers and to spur robotic transformative service research (RTSR). In so doing, this paper follows a conceptual approach that integrates findings from various domains: service research, social robotics, social psychology and medicine. Two key findings advanced in this paper are (1) a typology of robotic transformative service (i.e., entertainer, social enabler, mentor and friend) as a function of consumers' state of social isolation, well-being focus and robot capabilities and (2) a future research agenda for RTSR. The findings of this paper guide service consumers and providers and robot developers in identifying and developing the most appropriate social robot type for advancing the well-being of vulnerable consumers in social isolation. This conceptual study is the first to integrate social robotics and transformative service research by developing a typology of social robots as a guiding framework for assessing the status quo of transformative robotic service on the basis of which it advances a future research agenda for RTSR. It further complements the underdeveloped body of service research with a focus on eudaimonic consumer well-being.

Keywords: Social robots, Vulnerable consumers, COVID-19, Eudaimonic well-being, Robotic transformative service research

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4.1 Introduction

COVID-19 acts as a major disruptive factor for service consumers. The concerted world-wide quarantine measures that impose on consumers to live in social isolation have immediate and long-term detrimental psychological health consequences (Brooks et al., 2020). These negative effects are exacerbated for vulnerable consumer groups, particularly older adults and children (Holmes et al., 2020). Even with an easing of the COVID-19 measures, a significant share of vulnerable consumers likely continues to live under restricted social contact and suffers from durable negative psychological health outcomes (e.g., older adults who represent a high-risk group; World Health Organization, 2020a).

A promising avenue to counter the adverse consequences of social isolation for vulnerable consumers is provided by the field of social robotics (e.g., de Graaf et al., 2015). Social robots are physically embodied agents designed for assisting and engaging in social interactions with humans in their everyday lives (Fong et al., 2003). An example is Pepper, a social robot that can interact with humans through conversation and its touch screen. Social robots can provide service to consumers without human interaction and may thus be deployed to create uplifting changes for consumer well-being during COVID-19 and beyond.

Even though the past decade of service research has witnessed the foundation and surge of how service can transform the well-being of consumers (Anderson, 2010; Anderson et al., 2013; Anderson & Ostrom, 2015; Gustafsson et al., 2015), alongside an increasing accentuation of the role of robots in service (Čaić et al., 2018; Mende et al., 2019; van Doorn et al., 2017; Wirtz et al., 2018), a systematic integration of social robots and transformative service research (TSR) is still in a nascent stage. As a consequence, the question of how social robots might assist vulnerable consumers to attenuate, or even reverse the negative psychological health consequences of social isolation and advance well-being remains unaddressed.

The underlying paper draws from the fields of social robotics (e.g., de Graaf et al., 2015), medicine (e.g., Hawkley & Cacioppo, 2010), social psychology (Ryan & Deci, 2001), and service research (e.g., Anderson et al., 2013) to derive interdisciplinary insights on how social robot service may improve vulnerable consumer well-being when facing social isolation. In so doing, it aims to contribute to service theory and practice by advancing a social robot perspective of TSR: *robotic TSR (RTSR)*, which we define as the integration of social robot and transformative service research that focuses on well-being-relevant outcomes of consumer and employee interactions with social robots. First, this study synthesizes findings from social robotics based on a typology of robotic transformative service to derive an understanding of the status quo and future potential of transforming vulnerable consumer well-being in social isolation. Second, it extends this synthesis and identifies a future research agenda for the newly identified sub-area of *RTSR*.

4.2 COVID-19 and Social Isolation

Extended periods of social distancing and isolation can seriously deteriorate the psychological well-being of individuals (Brooks et al., 2020). The consequences of the worldwide measures to combat COVID-19 force consumers into a deficiency of social contact, or *objective* social isolation (Hawkley & Cacioppo, 2010; Steptoe et al., 2013). Though few individuals may lead solitary lives without feeling lonely, generally recent evidence documents a significant predictive effect of social disconnectedness on *subjective* social isolation (Santini et al., 2020). The latter is equated with loneliness, or the distress concerning the quality or quantity of one's social relationships.

In particular, this subjective state of social isolation is associated with severe negative implications for physical, psychological, and cognitive health (Hawkley & Cacioppo, 2010). Various longitudinal studies suggest subjective social isolation as a risk factor for physical health deterioration and mortality (e.g., Cacioppo et al., 2002; Holt-Lunstad et al., 2015; Steptoe et al., 2013). Further, it is associated with increased moodiness and depression (Cacioppo et al., 2006), faster cognitive decline, and an intensified sensitivity to social threats (Bassuk et al., 1999; Cacioppo & Hawkley, 2009). Subjective social isolation is most prevalent among children and older adults (Pinquart & Sorensen, 2001), making them a particularly vulnerable consumer group during COVID-19.

4.3 Vulnerable Consumer Needs and Well-Being

Consumer vulnerability can be described as "a state in which consumers are subject to harm because their access to and control over resources are restricted in ways that significantly inhibit their ability to function in the marketplace" (Hill & Sharma, 2020, p. 551). Thus, this paper focuses on those consumers who are especially prone to suffer mental health consequences during COVID-19; non-adolescent children before puberty and people of 65 years of age and older (Holmes et al., 2020), which will be simply referred to as children and older adults in the remainder of the paper (Kabadayi et al., 2020). Depending on their degree of agency and autonomy, these groups may particularly struggle with accessing services that can help them overcome suffering through resource losses (e.g., Henkel et al., 2017) and hence, they both deserve specific attention from service research and offer ample potential for service to positively transform their well-being (Anderson et al., 2013). Accordingly, the World Health Organization (2020) emphasized the potential repercussions of COVID-19 measures on the mental health of exactly these two vulnerable groups and advocated their guidance.

Research on well-being is broadly approached from one of two perspectives: hedonic and eudaimonic (Ryan & Deci, 2001). Hedonic well-being is equated with pleasure and happiness and often operationalized as satisfaction and positive affect or the absence thereof (Ed Diener, 2012; E. Diener & Lucas, 1999). The eudaimonic form defines well-being along a set of dimensions that promote meaning and self-realization (e.g., environmental mastery, personal growth, positive social relations; Ryff, 1989) to advocate fully functioning individuals (Rogers, 1963). Integrating both approaches, the underlying study explores the potential of service to promote the well-being of vulnerable consumers. Depending on the circumstances they are facing, vulnerable consumers may benefit most from services with an emphasis on hedonic (e.g., entertainment) or eudaimonic (e.g., life-coaching) well-being in order for them to overcome the negative consequences of social isolation and thrive in the marketplace. Yet, particularly eudaimonic consumer needs may become significantly more pronounced during periods of crises (Barnes et al., 2021). The next section discusses one particularly promising angle of how service can achieve this goal – by deploying social robots.

4.4 The Transformative Potential of Social Robots

As a consequence of COVID-19, human service delivery became potentially harmful or in its extremes even lethal to both service providers and consumers (Miriri, 2020). Hence, a particularly promising avenue for service research to support vulnerable consumers during COVID-19 and beyond lies in social robot service. Social robots may increase consumers' access to and control over resources and decrease their vulnerability without violating physical distancing or isolation in their pursuit of well-being (Henkel et al., 2017; Hill & Sharma, 2020). Indeed, findings from social robotics in the context of vulnerable consumers report various ways for social robots to promote well-being. For instance, robots that promote social connectedness (e.g., telepresence robots, socially assistive robots) may decrease objective and subjective social isolation for vulnerable consumers including older adults (e.g., Robinson et al., 2014) and children (e.g., Moerman et al., 2019).

Prior research shows that social robots can function as emotional and social actors (Čaić et al., 2020; de Graaf et al., 2015) with a clear transformative mission. They demonstrate social behavior, following the norms of human social interaction (e.g., touch, emotional reactions; Wang and Rau, 2019). With these abilities, social robots create social presence and are perceived as social agents (van Doorn et al., 2017), particularly by children (Kahn et al., 2012) and older adults (Heerink et al., 2009). There is ample evidence in the field of social robotics that vulnerable consumers in social isolation cannot only promote hedonic (e.g., cheering up), but also eudaimonic well-being. For instance, robots may stimulate environmental mastery and personal growth through advancing communication skills and learning experiences (Baxter et al., 2017; Crompton et al., 2018; Khaksar et al., 2021). They may also help form positive social relationships, such as assuming roles in socialization, companionship, developing emotional relationships, comforting, coping with stress, anxiety and other negative emotional experiences, and supporting ties with other people (Cañamero & Lewis, 2016; Crossman et al., 2018; D'Onofrio et al., 2019; Khaksar et al., 2016; Melson et al., 2009).

4.5 Robotic Transformative Potential in Times of COVID-19 and Beyond – A Typology

This section synthesizes findings in the social robotics literature that are relevant for the well-being of vulnerable consumers facing social isolation. Structuring the status quo and the required future roles of transformative robotic service along three dimensions resulted in four distinct types of robotic transformative service. As depicted in Figure 9, the types are a function of (1) the predominant state of social isolation (i.e., objective vs. subjective), (2) the desired or required well-being emphasis (i.e., hedonic vs. eudaimonic), and (3) robot physical and psychosocial capabilities. As theorized here, the transformative potential of social robots is dependent on future technological advancements, particularly for those consumers who encounter severe subjective social isolation and who require structural support to attain eudaimonic well-being goals. Importantly, the different types resemble the authors' interpretation of respective findings in the literature and they do not imply a corresponding construal from an emic perspective.

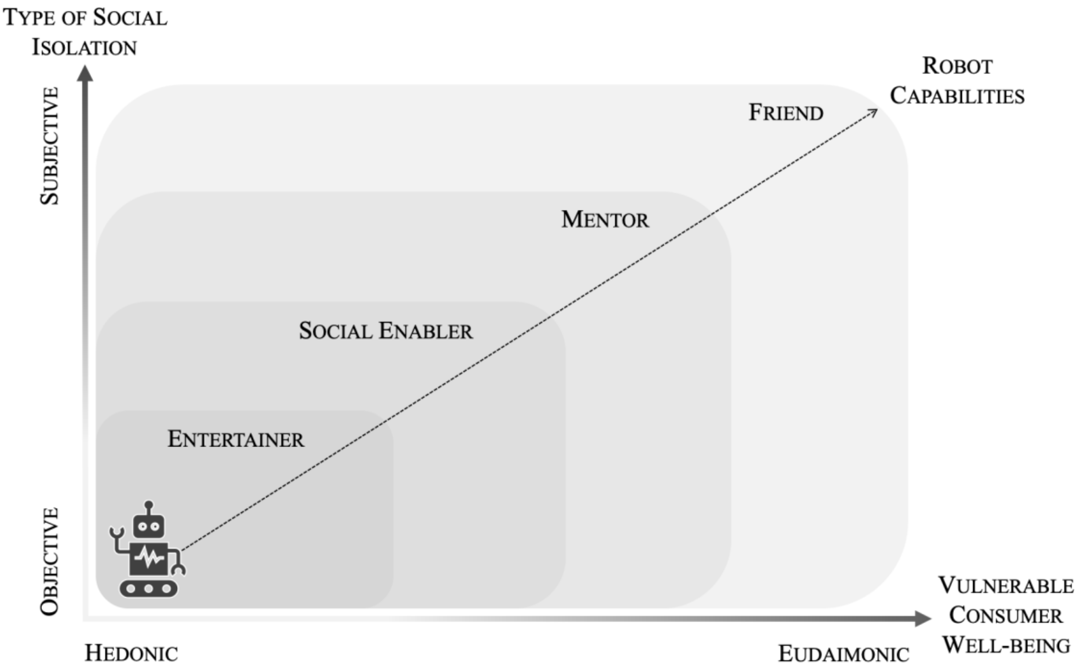

Figure 9: A Typology of Robotic Transformative Service to Counter Social Isolation

To date, robots with empathetic artificial intelligence (AI) (Huang & Rust, 2018) and human-level physical capabilities (Adalgeirsson & Breazeal, 2010; He et al., 2017) are not yet market-ready. However, exactly these types of social robots could provide complex transformative service, based on physical touch, social expressiveness, and relationship building (Huang and Rust, 2018). Below, we delineate in detail the transformative potential of each robot type for vulnerable consumers in social isolation, starting with those already being deployed to provide transformative service (i.e., entertainer, social enabler), and concluding with the types that are subject to current (i.e., mentor) and future (i.e., friend) research and development.

4.5.1 Market-Ready Robotic Transformative Service Roles

4.5.1.1 Entertainer

The entertainer robot might be most suitable to serve consumers who face imposed social disconnectedness and hence, merely experience minor psychological discomfort (e.g., boredom). The entertainer's social capabilities are limited since this robot type is pre-programmed to perform simple and repetitive social tasks. The entertainer may also be less equipped to console consumers through its touch due to its confined physical dexterity and basic embodiment. Its main transformative potential is hedonically oriented and lies in amusing consumers to increase their momentary affect as an end in itself (e.g., enjoyment when playing a game; Leite et al., 2008; dissipation in states of momentary solitude; Odekerken-Schröder et al., 2020). It might be deployed to prevent both older adults and children from experiencing minor psychological discomfort during isolation periods (Heljakka & Ihamäki, 2019). An example is Alibaba's DWI Dowellin, a small robot on wheels which entertains users by singing and dancing (Alibaba, 2020).

4.5.1.2 Social Enabler

As a social enabler, the robot may unfold its transformative potential by mediating social interactions for vulnerable consumers. The social enabler robot is not yet imbued with empathetic intelligence, however, with its improved physical capabilities (i.e., physical touch and mirroring social gestures) it can resemble authentic social contact (Rosenthal-von der Pütten et al., 2018). For instance, it can simultaneously display social contacts on screen and simulate their gestures and expressions through its artificial limbs (Adalgeirsson & Breazeal, 2010). During social isolation, this robot type may enable children to continue interacting with their peers and tutors and connect older adults with family, friends, and healthcare service providers from a distance. It might thus help socially isolated vulnerable consumers form and maintain positive social relations, and thereby improve academic performance (Furrer & Skinner, 2003) and affective well-being (Schmidt et al., 2019) for children, and diminish the negative effects of social isolation on physical (Cornwell & Waite, 2009) and mental (McInnis & White, 2001) health for older adults. Hence, the social enabler bears the potential to transform aspects of both hedonic and eudaimonic consumer well-being. An example is the MeBot, a small robot with two controllable arms and a big display that shows the interaction partner's face (Adalgeirsson & Breazeal, 2010).

4.5.2 Future-Oriented Robotic Transformative Service Roles

4.5.2.1 Mentor

Assuming a mentor role, transformative robotic service is predominantly directed at supporting vulnerable consumers in overcoming threats to their pursuit of eudaimonic well-being. During social isolation, both children and older adults are deprived of transformative, self-actualizing services which usually require the presence of a professional service provider (e.g., education, physio- and psycho-therapy). A mentor robot type may autonomously engage consumers on a professional, social, and empathetic level while exhibiting nearly human-level physical capabilities (e.g., navigation, touch, object manipulation). With such capabilities, mentor robots could embody school teachers and hobby instructors (Niemiec & Ryan, 2009) or physio-therapists (Bhuvaneswari et al., 2013).

Recent findings document that social educational robots can increase consumers' productivity, language skills, and physical, cognitive, and social–emotional learning experiences (Baxter et al., 2017; Crompton et al., 2018; Khaksar et al., 2021). Likewise, regular physical activity with mentor type robots has been shown to ensure older adults' mobility (Bhuvaneswari et al., 2013; Lopez Recio et al., 2013) prolonging their ability to live independently. Although vulnerable consumers may experience hedonic pleasure during these interactions (Čaić et al., 2019), mentor robots may particularly promote long-term eudaimonic well-being outcomes for children and older adults alike. While such robots are used in research, no fully autonomous version that integrates all mentor-type capabilities exists in the marketplace yet that could substitute a human service provider (Čaić et al., 2020). In the future, an example robot for children and older consumers could be physically advanced versions of ICP's Keeko (Low, 2018) or Pal Robotics' GrowMu (Georgiadis et al., 2016), respectively. Both robots combine human-like facial features with verbal communication abilities.

4.5.2.2 Friend

As a friend, the robot unfolds its transformative potential for vulnerable consumers who experience psychological distress (e.g., loneliness, lack of relatedness) due to both objective and subjective social isolation (Brooks et al., 2020). A friend robot may mitigate these negative consequences through quasi-social interactions. As envisioned here, this type of transformative robotic service would require an empathetic intelligence for rapport building and human-level haptic behaviors (e.g., touching, hugging) to provide solace through physical touch (Tanaka et al., 2007). As a friend, the robot could help alleviate the negative effects of social isolation by providing both hedonic and eudaimonic well-being in the form of genuine care and emotional comfort (Lehoux & Grimard, 2018), personalized service (Robinson et al., 2014; Sorell & Draper, 2014), and re-building self-esteem (Leite et al., 2012). Initial evidence suggests that children and older adults may perceive prototypes of such autonomous robots as social beings (Kahn et al., 2012) and friends (Cañamero & Lewis, 2016; Sinoo et al., 2018). While robots assuming a mentor role may predominantly provide eudaimonically-oriented professional transformative service, as genuine, loving companions friend type robots could cater to the entirety of well-being aspects (Crossman et al., 2018; Kachouie et al., 2014). In the future, such a robot might be a significantly advanced version of Pepper, equipped with an empathetic AI.

4.6 Discussion and Future Research Agenda

Vulnerable consumers routinely face adverse circumstances in the marketplace. With the advent of COVID-19, increased social distancing has raised the hurdles to participate in the marketplace for all consumers and it has exacerbated the social isolation of vulnerable consumers in particular. This study advances a typology of transformative robotic service that integrates work on social isolation (e.g., Hawkley & Cacioppo, 2010), well-being (Ryan & Deci, 2001), and social robotics (e.g., de Graaf et al., 2015) with the aim to cater to the underrepresented group for vulnerable consumers in service research (Rosenbaum et al., 2017).

The typology is derived based on two of the most affected vulnerable consumer groups during COVID-19: children and older adults (Holmes et al., 2020; World Health Organization, 2020a) and its main objective is to guide service researchers, practitioners, and consumers on the potential of robotic service to offset the negative consequences of social isolation (Brooks et al., 2020) now and in the future. Figure 10 provides an overview of the conceptual integration of the robot typology into the transformation of hedonic and eudaimonic well-being of vulnerable consumers in the (post-) COVID-19 reality. With an increasing level of sophistication of capabilities, social robots are already equipped to provide transformative service as entertainers and social enablers, and in the foreseeable future also as mentors. However, the full spectrum of eudaimonic well-being will likely only be provided by a friend-type robot which does not yet exist in the marketplace. We therefore encourage social robot research and development to focus on designing such a service with the aim to better support vulnerable consumers with a comprehensive focus on eudaimonic well-being.

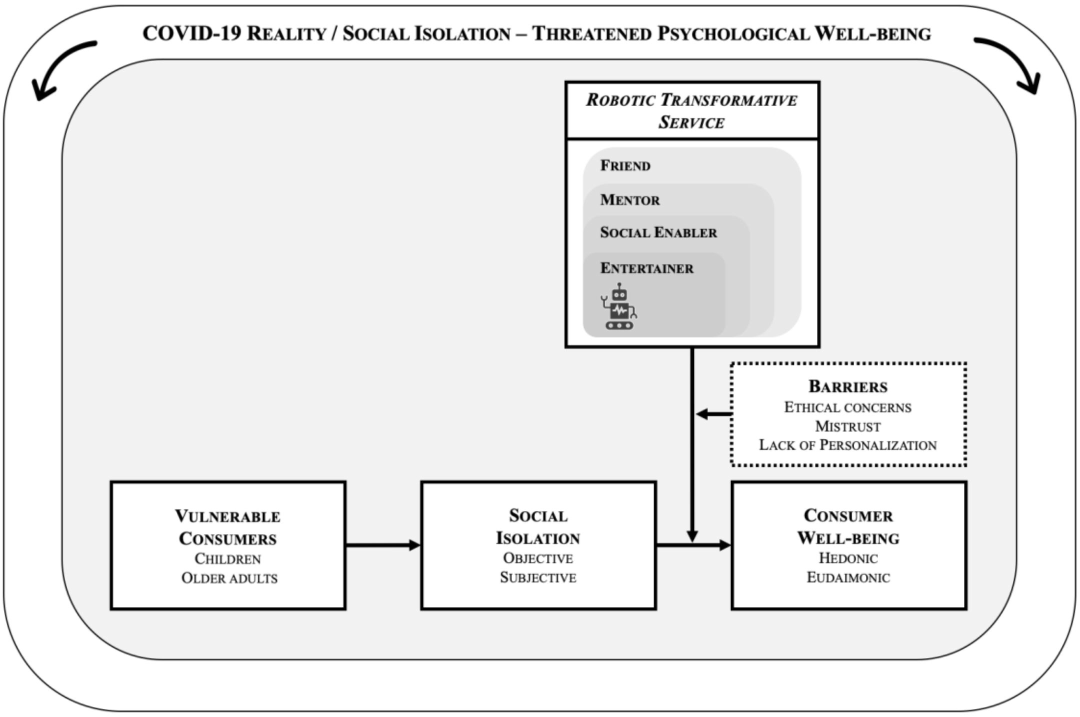

Figure 10: Robotic Transformative Service Infusion During Social Isolation

The theoretical integration of social robot service and well-being suggests a novel, interdisciplinary perspective on the role of service in creating uplifting changes for consumers (Anderson, 2010; Anderson et al., 2013; Anderson & Ostrom, 2015; Gustafsson et al., 2015). Traditionally, a majority of service research has documented predominantly ephemeral, positive (e.g., Oliver, 1997) or negative *hedonic* effects on consumer affect (e.g., Bougie et al., 2003) – mostly as an unintended consequence of service. This study offers an integrative well-being perspective to service and thereby also supplements research on the eudaimonic well-being of consumers (e.g., Guo et al., 2013; Henkel et al., 2017). Through identifying context-dependent (i.e., state of social isolation/well-being emphasis) transformative roles of social robots, the underlying paper identifies a new sub-area for TSR: *robotic transformative service research (RTSR)*.

In accord with the literature review in the field of social robotics on the various roles that transformative robotic service can assume in enhancing the well-being of vulnerable consumers, Table 6 advances an illustrative compilation of future research avenues for RTSR. The agenda is organized along three main topics: 1) the transformative potential of social robots as entertainers, social enablers, mentors, and friends, 2) barriers to robotic transformative service potential, and 3) eudaimonic consumer well-being. In two additional columns the table condenses the existing knowledge on each respective topic with exemplary research findings and outlines concrete future research avenues for RTSR. These questions are grouped in themes ranging from robot and service design, over consumer perceptions, ethical considerations, and the assessment of robot-facilitated well-being. Rather than providing an exhaustive overview, Table 6 is meant as a catalyst to stimulate research on RTSR.

The COVID-19 crisis offers a futuristic perspective on the changing role of service. While many services are provided remotely, some are suspended entirely (e.g., Hall et al., 2021). For those services that service consumers and providers are still able and required to co-create physically, social distance is the first priority (cf., Bove & Benoit, 2020). It is conceivable that consumers may continue to hold an increased sensitivity toward social interactions with service providers that outlasts COVID-19 (cf., Hazée & van Vaerenbergh, 2021), which may in turn also affect employee well-being (Tuzovic & Kabadayi, 2021). Eventually, these developments may surge service innovation (cf., Heinonen & Strandvik, 2021). A rapid adoption of automated service may be a consequence. While the underlying paper advances a typology of such robotic service to cater to the well-being of vulnerable consumers facing the abyss of the consequences of social isolation, in the future, transformative robotic service may be considered for creating uplifting changes in well-being for consumers at large.

Topic	What We Know	Future Research Agenda
Transformative potential of social robots as: ▪ **Entertainer** ▪ **Social Enabler** ▪ **Mentor** ▪ **Friend**	**Robot roles** ▪ Current state of knowledge indicates that users and caregivers consider that robots should **not aim to replace humans** but could only perform certain tasks (Lehoux & Grimard, 2018). ▪ Social robots can take **complementary roles** (e.g., motivational coach) and assist human caregivers in improving older adults' physical and psychosocial well-being (Čaić et al., 2020). ▪ Children can develop **friendly relationships** with robots as teachers and progressively **treat them as peers or see them as friends** (Cañamero & Lewis, 2016) rather than toys (Kanda et al., 2007) **Robot skills** ▪ Evidence suggests that in various child-related contexts social robots can be as successful as humans in terms of **comforting** (Meyns et al., 2019; Shahid et al., 2014). ▪ One size does not fit all - specific attention should be paid to the development of the **robot's social behavior and skills** beyond a mere functional support for the person (Bedaf et al., 2019). ▪ Social robots can provide **personalized services** (Robinson et al., 2014; Sorell & Draper, 2014), **emotional comfort** (Lehoux & Grimard, 2018), and can help **rebuild self-esteem** (Leite et al., 2012). **Fulfillment of psychosocial needs** ▪ Social robots can strengthen **older adults' sense of autonomy** by making them less dependent to staff and formal care, closer to friends and families outside the facilitations, more functionally available in doing tasks (Pirhonen et al., 2020). ▪ Social robots have potential to **reduce older adults' social vulnerability** (Khaksar et al., 2016).	**Service context** ▪ What context-related factors play a role in robotic transformative service? ▪ What well-being-relevant service provider roles can be substituted vs. augmented by social robots? **Robot design** ▪ How does the morphology of social robots (i.e., human-like, animal-like, machine-like) impact their transformative potential for diverse groups of vulnerable consumers (e.g., children, older adults, chronically ill, bedridden patients)? ▪ Which robot design aspects (e.g., appearance, tone of voice, gaze) lead to optimal well-being outcomes? **Robot social interaction capabilities** ▪ What is the impact of automated social presence on the transformative potential of robots? ▪ Can the fulfillment of psychological needs serve as an explanatory mechanism of how social robots unfold their transformative potential? ▪ Can social robots be equally successful in building positive social relations for adults as they are for children? **Consumer attitudes** ▪ There is strong empirical evidence in various service contexts that documents negative attitudes of consumers toward automation (e.g., Longoni et al., 2019) and robots in particular (Wang et al., 2015). What role do these attitudes play in transformative robotic service interactions? ▪ What is the effect of COVID-19 on consumer attitudes toward social robots - have these attitudes reversed in the new "1.5m-society"? **Consumer acceptance** ▪ What drives the acceptance of different social robot roles among vulnerable consumers (i.e., individual level) and their care networks (i.e., collective level)? ▪ Which haptic behaviors (e.g., touching, hugging) are deemed appropriate by vulnerable consumers? How can such behaviors be leveraged for increased consumer acceptance?

Topic	What We Know	Future Research Agenda
Barriers to robotic transformative potential	**Dehumanization and loss of privacy** ▪ Older adults fear social robots would **substitute their nursing staff** and even further increase their loneliness (Čaić et al., 2018). ▪ Ethical considerations include **loss of human contact**, increased feeling of objectification and loss of control, loss of privacy and personal freedom as well as **deception** and infantilization (Sharkey & Sharkey, 2012). ▪ Contextual factors of **privacy, trust and perceived behavioral control** have a negative impact on continued use of social robots (de Graaf et al., 2015). **Need for personalization** ▪ **Personalization** is critical to emotional exchanges with robots (Henkemans et al., 2017; Kim et al., 2013). ▪ Sandygulova and O'hare (2018) found that, **gender matching** is important for robot preference. Children choose social robots with the same gender. ▪ Social robots' success in decreasing older adults' social vulnerability depends on social robot **enablement** and **mediation**. Social robot enablement includes older consumers' trust in social robots, their perceptions about the costs related to social robots, and their concerns about safety. Social robot mediation includes personalized service, delivery, entertainment, and connectivity provided by social robots (Khaksar et al., 2016).	**Ethical concerns** ▪ To what extent *can* and *should* robots take responsibility over children and/or older adults as care givers? ▪ To what extent is deception an alarming ethical concern? Can we identify robot design and behavior characteristics that lead to consumer deception? ▪ Research suggests that sometimes meaningful professional relationships or even (commercial) friendships might emerge from service interactions (e.g., Price & Arnould, 1999; Yim et al., 2008). Can the robot-as-friend type assume a similar role? And if yes, is it desirable and ethically tolerable to deploy social robots as human substitutes for consumers with low agency? ▪ Can one robot type (e.g., friend) cater to all consumer needs at once, or is the most effective transformative robotic service context dependent? **Mistrust** ▪ What are the robot design barriers that make robots less trustworthy and humane than real humans in child and older adults care? ▪ How do different robot morphologies affect consumer trust? ▪ How will robots equipped with a truly empathetic AI be perceived and adopted? And how can we mitigate the effects of the Uncanny Valley (Mori et al., 2012)? **Lack of personalization** ▪ What are the preferred gender options for different robot types (e.g., mentor vs. friend)? Or should the gender be matched with the gender of a vulnerable consumer? ▪ What other personalization aspects (e.g., tone of voice, lokk) are relevant for RTSR? **Other** ▪ What are other unintended consequences of robotic transformative service on different groups of vulnerable consumers (e.g., children, older adults, chronically ill, bedridden patients)?
Eudaimonic well-being	**Psychosocial health** ▪ Social robots increase children's **positive mood** after stressful tasks (Crossman et al., 2018). ▪ Social robots strengthen children's **motivations and positive emotions** in therapy (Meyns et al., 2019). ▪ In a healthcare context, children **smile more, cry less** in company of a social robot (Beran et al., 2015).	**Measuring well-being** ▪ How can well-being be measured for different vulnerability groups? And which, if any, new metrics need to be considered? ▪ What are the long-term effects of robotic transformative service on well-being outcomes? ▪ Will longitudinal studies support the claims of improved psychological well-being of vulnerable groups when compared to those without social robots during extended periods of social isolation?

Topic	What We Know	Future Research Agenda
	▪ Social robots improve children’s **openness and mood** in hospitals, contributing to their **self-management** (Looije et al., 2016). **Personal growth** ▪ In children-related contexts, several studies show that social robots increase **productivity, learning and success** of children in doing daily tasks (Baxter et al., 2017; Khaksar et al., 2021; Wu et al., 2015). ▪ Playing educational games, social robots support children’s **social and cognitive development** (Tanaka et al., 2007). ▪ Social robots instructing older adults in physical tasks and cognitive exercises improve their **physical and mental health** (Bhuvaneswari et al., 2013; Lopez Recio et al., 2013), prolonging older adults’ ability to live independently.	▪ Can positive robotic well-being implications for older adults and children be generalized to other vulnerable consumers? **Well-being trade-offs** ▪ How can positive outcomes of interactions with social robots (e.g., eudaimonic well-being) outweigh negative consequences (e.g., privacy issues, dehumanization) for vulnerable consumers during COVID-19 and beyond? ▪ Under what circumstances is deploying social robots in vulnerable consumer settings detrimental to consumer well-being? For instance, may there be conditions (e.g., absolute isolation) under which robots might reinforce consumer subjective loneliness? **Different dimensions of well-being** ▪ To what extent are the hedonic and eudaimonic perspectives on well-being reconcilable in robotic transformative service? ▪ What consumer idiosyncrasies are important to consider for an effective robotic transformation of consumer well-being?

Table 6: Status Quo and Future Research Agenda on RTSR in Times of COVID-19 and Beyond

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5. Collaborative Intelligence Systems – How to Retain Employee Responsibility Taking when Co-Producing Service with AI Systems[7]

Abstract

Organizations increasingly make use of artificial intelligence (AI) systems to co-produce services with employees. While such systems bring efficiency advantages, they can also diminish employee responsibility taking for jointly produced outcomes. This research aims to shed light on which system features constitute a collaborative AI system in service co-production making it a collaborative intelligence (CI) system, which we assume to foster employee responsibility taking. To this end, we first conduct an extensive literature review and a qualitative study to identify relevant CI system features (i.e., reciprocal strength enhancement, engagement, transparency, process and outcome control). Drawing from service encounter needs theory, we then posit that the effect of CI systems on employee responsibility taking is mediated by the extent to which employees' psychosocial needs are fulfilled. Using scenario-based experiments with analysts (N = 124) and customer advisors (N = 185), we demonstrate that the way in which CI systems drive employee responsibility taking differs between these groups because of different needs being addressed. Our research contributes to service literature by introducing CI systems in the context of technology-infused service co-production and empirically testing its effects on employee outcomes. Service scholars and managers benefit from a blueprint for designing CI systems.

Keywords: Collaborative intelligence systems, Artificial intelligence, Employee needs, Outcome responsibility, Financial services

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[7] **Current Status of the Paper:**

A revised version of this paper is in the second round of review in an A-listed journal published by SAGE Publishing. The publisher and the editor in chief permit including the article of Chapter 5 in its current form in the print version of this thesis. The abstract as well as the formatting of this paper have been adjusted to fit the formatting of the other sections.

5.1 Introduction

Today, technology based on artificial intelligence (AI) supports many service employees, such as recruiters in screening and deciding upon fitting applicants (Marr, 2019) or analysts in deciding upon credit loans (DBS Bank, 2021). These AI systems may have collaborative features such that service outcomes are co-produced based on contributions of employees and AI (Bock et al., 2020). While AI systems in general are expected to free service employees from tedious tasks and thus have positive effects on service firm efficiency (Davenport et al., 2020; Marinova et al., 2017), there might be a dark side too: co-producing service outcomes with AI systems can diminish employees' sense of problem ownership and responsibility taking (Santoni de Sio & Mecacci, 2021).

Employee responsibility taking is crucial to reduce the risk of erroneous decisions and tarnished customer relationships, especially in highly regulated and trust-based service processes and sectors (Alation, 2017; Brooks, 2021; Ghosh, 2017; Kokina et al., 2019). For instance, in financial services, creditors rely on AI systems that systematically put lower-income and minority groups at a disadvantage when supporting employees in deciding upon a loan (Heaven, 2021). As another example, when partnering with an AI recruiting tool that appeared to favor male applicants, Amazon's HR employees allegedly took no responsibility when they based their candidate preselection on the system's output (Manyika et al., 2019). Also, physicians might transfer some responsibility to an AI system when diagnosing diseases (Hsu, 2017), even though an incorrect diagnosis may have serious well-being consequences for the patient and potentially cause legal problems for the physician's employer (Semigran et al., 2016). Thus, while bringing performance advantages, AI systems might also detach employees from the decision-making process, leading them to take less responsibility and facilitate socially and economically undesirable outcomes.

Thus far, relatively little is known about why employees' responsibility taking diminishes when they co-produce services with AI systems. Service research has focused on human-AI collaboration (e.g., Bromuri et al. 2021), but not in combination with responsibility taking. The latter has been discussed in service co-production (e.g., Bendapudi & Leone 2003), but not when AI plays a part in this process. In the context of technology-infused service encounters, the issue of responsibility has mostly been considered as customers attributing a service outcome to a service robot (Belanche et al., 2020; Jörling et al., 2019), rather than employees' responsibility taking for a task or outcome when working with an AI system. Furthermore, while we know that customers' psychological needs may act as a driver of perceived responsibility in automated services (e.g., need of control; Jörling et al., 2019), knowledge on what AI system design features fulfill relevant psychosocial needs of service employees is scarce and only conceptual in nature (Zerilli et al., 2019). In sum, literature does not give a clear picture on the process of employees' responsibility taking when co-producing services with AI.

To address the current obstacles, the aim of this research is to understand how collaborative AI systems, which we refer to as *collaborative intelligence (CI) systems* (cf., Epstein, 2015), affect employee responsibility taking for co-produced service outcomes. We specifically focus on the role of employees' need fulfillment in this relationship. Accordingly, we posit two central research questions:

1. *What are the features that characterize AI systems as CI systems?*
2. *How does working with CI systems relate to responsibility taking of employees?*

To answer our research questions, our work consists of two studies. In Study 1, we develop the concept of a CI system for service co-production by conducting a comprehensive literature review and a qualitative study (i.e., 14 semi-structured interviews). Jointly, these efforts identify the key features of an AI system that facilitates collaboration with employees. In Study 2, we empirically investigate if and how CI, which are characterized by the identified key features, systems relate to employee responsibility taking. To do so, we build and test a conceptual model using service encounter needs theory (SENT; Bradley et al., 2010). We make the following contributions to literature.

First, we contribute to work on human-AI collaboration in service settings by delineating the conceptual domain of a CI system, identifying its idiosyncratic features, and demarcating it from related constructs and concepts, such as hybrid intelligence (Dellermann, et al., 2019b), collective intelligence (Gavriushenko et al., 2020), and human-AI symbiosis (Jarrahi, 2018). By clearly defining CI system features we provide service scholars and managers with a blueprint for designing such systems in the context of service co-production.

Second, while scholars have outlined human-AI collaboration outcomes on the firm level (e.g., Wilson & Daugherty, 2018) or the dyadic level (i.e., the quality of the jointly made decisions; Dellermann et al. 2019b), we consider employee responsibility taking as an important outcome on the individual level. In fact, in the process of using AI to improve service performance, the responsibility concept may conceptually precede the quality of joint decision making, which may then influence dyadic- and firm-level consequences. By providing insights into AI's relationship to this individual-level outcome, we further complete the chain of effects that originates in human-AI collaboration and ends, ultimately, at firm performance.

Third, drawing on SENT (Bradley et al., 2010), we empirically investigate how CI systems relate to employee responsibility taking through satisfying (or not) the following employee needs: need for control, cognition, competence, and justice. We contribute to literature by showing that CI system design has a positive effect on fulfillment of all needs considered, indicating that SENT can be transferred to the context of employee-AI service co-production. We also advance knowledge on the mechanisms of responsibility taking in automated service settings (Belanche et al., 2020; Jörling et al., 2019) in that our research shows that when employee need for control is met, responsibility taking is enhanced.

Finally, we add insights to a stream of literature that has concentrated on identifying personal and task characteristics as contingency factors in technology acceptance and use (e.g., Blut et al., 2016; Brown et al., 2010; Park et al., 2014). Specifically, we demonstrate that the effect of CI systems on responsibility taking differs between employees with different job profiles (i.e., analysts and customer advisors), indicated by different needs being addressed by the system. In contrast to hard-to-observe employee traits such as empathy (e.g., Wilder et al., 2014), job profiles are readily identifiable by managers, allowing more direct facilitation options for resource allocation to CI design features to achieve successful CI system implementation.

Next, we present Study 1 and Study 2 and discuss managerial and theoretical implications of our research. We close this paper with a future research agenda in the domain of collaborative intelligence.

5.2 Study 1: Conceptualizing Collaborative Intelligence Systems for Service Co-Production

Service co-production is the joint production of service outcomes (Bendapudi & Leone, 2003; Meuter & Bitner, 1998). In the traditional sense co-produced service outcomes are generated by joint inputs of human frontline employees and customers (Oertzen et al., 2018). The infusion of AI systems in organizations offers a different view to service co-production (Henkel et al., 2020). Here, employees and AI systems build a symbiosis by complementing each other while working on a joint task (Paschen et al., 2020). In this co-producing role, the AI system becomes a collaborative intelligence system (CI system).

To define the conceptual domain of CI systems, we conducted a comprehensive literature review across scientific topic areas. Our aim was to gain an overview of how collaborative intelligence and related constructs have been defined and to identify the most relevant features for successful human-machine service co-production (cf., MacKenzie et al., 2011). We systematically searched six research databases (i.e., ACM DL, EconBiz, EbscoHost, IEEE Xplore, Scopus, and a national database on academic publications in social sciences) to identify peer-reviewed articles that were written in English and focused on collaboration of humans and AI. Specifically, we used the following search term: *collaborat* AND (AI OR intelligence)*. The search revealed a total of 188 articles of which 39 qualified for further investigation, because they focused on collaboration of humans and AI in a business context where outcomes are jointly produced and/or they indicated relevant system features. Additionally, we cross-checked the reference lists of these included articles and identified another eight relevant articles. We provide a full list of the 47 considered articles in Appendix G.

In our final set, six research articles provide a clear definition of CI. Table 7 depicts these concepts and their relevant details. The definitions not only differ in the features they include but also in the unit they refer to. Three CI definitions describe the combination of human and artificial intelligences per se (Gill, 2012, Huang & Rust 2021; Martin & Azvine 2018), while Wilson and Daugherty (2018) define CI as the outcome of a combination of human and artificial intelligence within an organization, and Zhong et al. (2015) utilize the CI term to describe the degree of the collaboration ability of humans and AI systems. Only Epstein's (2015) CI definition refers to an AI system. In combination with information drawn from our analysis of relevant articles that do not specifically use the term CI, we identify five focal features of CI systems: reciprocal strength enhancement, engagement, transparency, process control and outcome control.

Study	Definition	Unit	Context	General Construct Properties/Features
Huang and Rust (2022)	Combination of different levels of human and artificial intelligences for marketing tasks. "The view that AI can have multiple intelligences gives rise to multiple complementary ways of implementing collaborative AI". (p. 212)	Combination of human and artificial intelligence	Marketing tasks	▪ Complementary intelligences/strengths
Martin and Azvine (2018)	"Collaborative intelligence involves a combination of human and machine-based analysis, in which humans focus on higher-level tasks involving insight and understanding, whilst machines deal with gathering, filtering and processing data into a convenient and understandable form. (…). CI is a term used to describe any system where processing is shared between humans and machines." (p. 2589)	Combination of human and artificial intelligence	Data processing/analysis	▪ Complementary skills/strengths
Gill (2012)	"Collaborative intelligence characterizes multi-agent, distributed systems where each agent is uniquely positioned, with autonomy to contribute to a problem-solving network. (p. 161)"	Combination of human and artificial intelligence in a network	Problem-solving in multi-actor networks	▪ Complementary skills/strengths
Wilson and Daugherty (2018)	Result of AI augmenting human employees in performing a task. "Firms achieve the most significant performance improvements when humans and machines work together (…) and actively enhance each other's complementary strengths". (p. 4)	Outcome of combination of human and artificial intelligence	Different tasks in organizations to achieve firm goals	▪ Complementary skills/strengths enhancement ▪ Human in control
Zhong et al. (2015)	"In the context of Internetworked e-Work, we define Collaborative Intelligence (CI) as a measure to calculate the collaborability (collaboration-ability) of agents (…). CI is a measure of an agent's capability to perceive and comprehend new information, share required resources, information, and responsibilities with other peers to resolve new local and global problems in a dynamic environment." (p. 70)	Degree of collaboration ability of human and AI system	Problem-solving of human and AI in e-Work	▪ AI and/or human actively engage (joint problem solving)
Epstein (2015)	"(…) a collaborative intelligence (CI) partners with a person to achieve the person's goals. The assumption is that some subtasks are more reasonably delegated to the person, and others to the computer. A CI is intended not to substitute for a human employee, but to engage in (different) tasks with one (…) and is by definition more concerned with an appropriate and supportive division of labor; it is an active, not a passive, collaborator (…) and requires the ability to collaborate on a common goal." (pp. 41-45)	AI system	Employee augmentation with AI for different tasks	▪ AI actively engages user ▪ AI serves user and their needs ▪ Human in control (outcome) ▪ Transparency for human
Our CI system Concept	We define collaborative intelligence systems "AI systems that co-produce a service with employees in a collaborative way as a result of five key features: reciprocal strength enhancement, engagement, transparency, process control and outcome control."	AI system	Service co-production	▪ Complementary strength enhancement ▪ AI actively engages user ▪ Human in control (process) ▪ Human in control (outcome) ▪ Transparency for human

Table 7: Collaborative Intelligence Definitions in Literature

Reciprocal Strength Enhancement. The majority of analyzed articles emphasizes that successful human-AI collaboration leverages the strength of each actor. Thus, when humans and AI systems collaborate, each actor brings in their respective strengths which complement and strengthen each other (Wilson & Daugherty, 2018). For example, an AI system may provide big data analyses which, on the one hand, support employees in a decision and, on the other hand, gives them more time for solving problems that require creativity. By feeding decisions or ideas back into the system, the underlying algorithms learn employee preferences and improve their advice and performance over time.

Engagement. For an AI system to be perceived as collaborative, it should actively engage users to co-produce service (e.g., Epstein, 2015). For example, a CI system could pro-actively ask employees' opinion on a crossroad in the process towards a task outcome (e.g., via a chat module). A CI system should also engage employees by actively asking them for feedback on previous task outcomes.

Transparency. As a third feature, a CI system in service co-production should be transparent. A CI system can be described as transparent if it supports the user in understanding the way an advice was conceived and when the system explains the outcomes of its analyses (e.g., Epstein 2015; Lee et al. 2019). For example, a user may be informed about the underlying data and parameters that led to an output.

Process Control. To foster collaboration in service co-production, CI systems should provide users control over the service process. This control refers to the ability of the user to influence what evidence or data is considered by the CI system and the rules by which the output is generated (Lee et al., 2019; Lui & Lamb, 2018; Paschen et al., 2020). Employees would hence have the option to, for example, include or exclude certain parameters that lead to analysis outcomes.

Outcome Control. Finally, we identify the feature of outcome control as relevant for CI systems from extant literature. Outcome control allows employees to appeal or modify the outcome of an analysis once it has been made (Epstein, 2015; Lee et al., 2019; Lui & Lamb, 2018). Thus, the final decision would lie in the human counterpart of a CI system.

Finally, we engaged in a qualitative study by conducting 14 semi-structured interviews with practitioners. The aim of this study was twofold. First, we aimed to corroborate our previously identified features and to find, potentially, system features that might have not been discussed in literature yet, but are relevant in practice. Second, the interviews served as a validation study of our scenarios further described in Study 2.

The sample consisted of practitioners working in the financial sector and in different roles (i.e., analysts, customer advisors, managers). Interviewees had an average of 10 years tenure and were highly experienced in working with professional (partly AI-enabled) software which enables them to voice wishes and needs when collaborating with AI systems. The financial sector is well suited for our research purposes as there are many use cases for AI and employees are used to working with big data and support software (McKinsey, 2021).

The interview guide was designed based on the aims of Study 1 and was slightly adapted after a pretest with one practitioner. The final guide included five parts: (1) Warm-up questions and questions regarding the interviewee's general understanding of AI technology and working with AI systems, (2) questions regarding the general expectations when collaborating with AI systems, (3) questions related to specific expectations on AI system design features that foster collaboration, (4) understanding of the five identified features and ideas of how to translate them to system design, and (5) an opportunity to voice additional aspects that were not mentioned before. The interviews lasted 50 minutes on average, were recorded and then transcribed. To analyze the data we leveraged template analysis, where primary codes are defined a priori (i.e., CI system features identified in literature) and may be adapted in the process (King, 1998). The data was analyzed by two researchers along pre-defined coding rules. Changes in codes and differences in coding were discussed and resolved by consensus. While the interviews did not reveal any new features, they supported our selection of the identified features and specified how these features could be implemented in AI systems in service practice (see Table 8). We depict sample characteristics, the interview guide, transcription rules, and example quotes per CI system feature in Appendices H-L.

In synthesizing the information from our comprehensive literature review and qualitative study, we define collaborative intelligence systems as:

"*AI systems that co-produce a service with employees in a collaborative way as a result of five key features: reciprocal strength enhancement, engagement, transparency, process control and outcome control.*"

Furthermore, as can be distilled from their descriptions and summarized in Table 8, the five features are unique but, depending on their implementation in the system, may have slight overlap or even complement each other. We hence conceptualize the CI system as a holistic yet multi-dimensional phenomenon, such that the more the five features are presented, the more we call the system a CI system rather than "just" AI system.

Feature	Definition	Feature Design
Reciprocal Strength Enhancement	CI systems are designed in a way that leads to reciprocally strength enhancement of human users and CI systems as each other's complementary strengths are leveraged (Dellermann, et al., 2019a; 2019b; Epstein, 2015; Gill, 2012; Huang & Rust, 2022; Martin & Azvine, 2018; Wilson & Daugherty, 2018; Zhong et al., 2015).	▪ CI systems deal with parts of joint tasks that humans cannot take on easily (e.g., big data analysis), hence enable employees to focus more on their strengths (e.g., creative thinking) ▪ User regularly provides feedback to a CI system's output to improve its prediction power, the CI system communicates its improvement; employees learn and improve their own performance over time
Engagement	CI systems actively engage with human users in the process of service co-production (Epstein 2017; Martin and Azvine 2018; Lyons et al. 2021).	▪ CI systems actively ask users' opinion on a crossroad (e.g., in decision making processes) ▪ CI systems actively ask for feedback on their outputs
Transparency	CI systems are transparent which allows the human user to understand the way a CI system draws conclusions and explains the outcomes of its analyses (Epstein, 2015; Lee et al., 2019).	▪ CI systems provide information on parameters a solution/decision is based on ▪ CI systems explain the outcomes of their analysis
Process Control	CI systems provide process control which allows the human user to influence what evidence or data is considered by the CI system and the rules by which the output is generated (Lee et al., 2019; Lui & Lamb, 2018; Paschen et al., 2020).	▪ User decides on data input ▪ CI systems provide option to change parameters of the decision-making process
Outcome Control	CI systems provide outcome control which allows the human user to appeal or modify the outcome or decision of a CI system analysis once it has been made (Epstein, 2015; Lee et al., 2019; Lui & Lamb, 2018).	▪ CI systems provide user with control over the final decision in decision or solution processes

Table 8: Features of Collaborative Intelligence Systems

To ensure that our CI system represents a unique concept, we demarcate it from six related concepts identified through our literature review, namely *hybrid intelli-*

gence (Dellermann et al. 2019a; 2019b), *human-AI symbiosis* (Jarrahi, 2018), *collective intelligence* (Gavriushenko et al., 2020), *intelligence augmentation* (Larivière et al., 2017), *human-AI teaming* (Dubey et al., 2020), and *machines-as-teammates* (Lyons et al., 2021; Seeber et al., 2020). We therefore extracted these concepts' corresponding definitions, distilled general properties and AI system features, if applicable, and outlined the differences to our CI systems concept (see Table 9). The related concepts are different from our CI system concept because most of them do not define an AI system, but focus on the joint collaboration of humans and AI systems per se (e.g., Jarrahi 2018) or the human perception of the collaborativeness of an AI system (Lyons et al. 2021) instead of the AI system itself. Thus, they do not detail clear CI system features. Even though Seeber et al. (2020) and Dellermann et al. (2019a; 2019b) touch upon AI design, both focus on describing meta-design categories (e.g., appearance, conversation) rather than their underlying function.

In answering our first research question we show that extant research has already produced a variety of definitions for the concept of collaborative intelligence. In addition, literature has put forth related concepts. We built on extant CI studies and qualitative data to unify extant perspectives and more clearly conceptualize a CI system in a service co-production setting. To better understand the effects of our conceptualized CI system on employee outcomes, in particular on employee responsibility taking, we next develop our conceptual model and empirically test it in two scenario-based experimental studies.

Concept	Definition	Unit	General construct properties/features	Differentiation from CI systems
Hybrid Intelligence (HI) *Kamar (2016); Dellermann et al. (2019a ;2019b)*	"We envision hybrid intelligence systems, which 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 (pp. 274-276).	Human-AI system	▪ Enhanced results through collaboration in complex tasks ▪ 4-main concept properties (i.e., human-AI interaction, AI-human interaction, learning paradigm, task characteristics)	▪ Focuses only partly on AI design features (cf. meta-property: AI-Human interaction) ▪ Lays general foundations for design of HI-systems in different fields
Human-AI Symbiosis *Jarrahi (2018)*	Human-AI symbiosis means interactions between humans and AI can make both parties smarter over time. (…) whereby this article (…) focuses on the comparative advantages held by humans and machines in relation to the three characteristics that affect almost all organizational decision making. (pp. 583-584)	Human-AI system	▪ Enhancing each other's strengths through symbiosis ▪ Focus on organizational decision-making; combination of humans and AI skills in accordance with 3 central properties (i.e., uncertainty, complexity, equivocality)	▪ No focus on AI design features ▪ Specific focus on organizational decision-making context
Collective Intelligence *Gavriushenko et al. (2020)*	"We consider Collective Intelligence as a hybrid of human intelligence collaborating with several types of personal digital assistants (intelligent agents, advisors, clones, twins, etc.). (…) We treat the concept of Collective Intelligence in terms of how AI and Human are able to assist one another in the education process." (p. 303)	Human-AI system	▪ Collaborating with a variety of different digital assistants ▪ Goal to learn from each other how to learn	▪ No focus on AI design features ▪ Specific focus on learning process of human and AI
Intelligence Augmentation *Larivière et al. (2017)*	"Intelligence Augmentation (IA), reflects situations in which technology supports human thinking, analysis and behavior. In other words, technology can be used in tandem with employees to provide a better service encounter outcome." (p. 240)	Human-AI system	▪ Enhance results through collaboration in service provision ▪ Focus on service encounter outcomes	▪ No focus on AI design features
Human-AI Teaming (HAT) *Dubey et al. (2020)*	"Systems that have the ability to accomplish complex goals by combining human and artificial intelligence to collectively achieve superior results by capitalizing the strengths of each other and continuously improve by learning from each other (cf. hybrid intelligence). (…) We model human-AI systems as multi-agent systems to address scale of real business applications." (p. 2)	Human-AI system (multiple-agents)	▪ Enhanced results through multi-agent collaboration in complex tasks ▪ 4 general meta properties (i.e., task characteristics, learning paradigm, teaming properties, trust)	▪ No focus on AI design features ▪ Focus on collaboration in multi-agent systems
Machines as Teammates (I) *Lyons et al. (2021)*	The notion of machines as teammates is (…) "based on the model of autonomous agent teammate-likeness (AAT), that shows the concepts of agency, benevolence, interdependence, communication richness, synchrony, and team focus are the key, factors in shaping the perception of a technology as a teammate vs. as a tool (...)" (p. 5)	Human	▪ Human perception of AI as teammate ▪ 6 antecedents that foster this perception (i.e., agency, benevolence, interdependence, communication richness, synchrony, team focus)	▪ No focus on AI design features per se but human perceptions of AI ▪ No clear enhancement of each other's strengths
Machines as Teammates (II) *Seeber et al (2020)*	"(…) we defined machines as teammates (MaT) as those technologies that draw inferences from information, derive new insights from information, find and provide relevant information to test assumptions, debate the validity of propositions offering evidence and arguments, propose solutions to unstructured problems, and participate in cognitive decision-making processes with human actors". (p. 3)	AI system	▪ Enhanced results through collaboration ▪ 6 design features for machines (i.e., appearance, sensing & awareness, learning & knowledge processing, conversation, architecture, visibility & reliability, design methodology)	▪ AI design features are general categories and not clearly elaborated for a specific AI application ▪ No clear enhancement of each other's strengths

Table 9: Differentiation of Related Concepts from Collaborative Intelligence Systems

5.3 Study 2: The Effects of Collaborative Intelligence Systems on Employee Responsibility Taking

5.3.1 Literature Review and Theoretical Background

5.3.1.1 Employee-AI Collaboration as Service Co-Production

Although still in a nascent stage, there are some empirical studies that give insights into the intricacies of employee-CI system collaborations. For instance, factors that determine collaboration success of humans and AI systems include technology-related factors (e.g., autonomy and social presence; Paluch et al., 2022), human actor-related factors (e.g., personal characteristics; Meissner et al., 2021; hedonic motivation; Ali et al., 2022; AI aversion; Kim et al. 2022; occupational identities; Pemer, 2021), and context- or task-related factors (e.g., job type; Paluch et al., 2022; organizational environment, Meissner et al., 2021; task type, Sampson, 2021). Additionally, while current research identifies the positive effects of employee collaboration with CI systems, such as increased firm performance (e.g., Paschen et al., 2020; Wilson & Daugherty, 2018) the potential negative effects such as decreased responsibility taking have been underexposed.

Some research has also hinted at *mechanisms* that drive positive outcomes of human-CI system collaboration. For example, Paluch et al. (2022) identify that the willingness of employees to work with service robots seems highly dependent on the employee's control perception over the robot. Henkel et al. (2020) show that an AI system that supports frontline employees in identifying customers' emotional shifts during calls stimulates employee well-being through perceived goal attainment. Moreover, in an educational setting Kim et al. (2022) show that AI systems may improve learning outcomes because educators better adapt to students' individual needs.

These initial efforts partly point to the importance of human need fulfillment to explain the relationship between CI system design and employee outcomes. In Study 2**,** we build on these insights and use service encounter needs theory (SENT; Bradley et al., 2010) to further conceptualize this relationship.

5.3.1.2 Responsibility Taking in Service Co-Production with Collaborative Intelligence Systems

Responsibility taking in service co-production is defined as the extent to which one of the involved parties feel a sense of ownership for the outcomes of a jointly produced service outcome (Bendapudi & Leone, 2003; Botti & McGill, 2011). Mostly

building on attribution theory (Kelley, 1967), researchers have especially focused on the attribution of responsibility in the case of positive (e.g., Wolf & McQuitty, 2011) or negative (e.g., Choi & Mattila, 2008) service outcomes and the consequences for service providers (e.g., increased customer satisfaction, Tsiros et al., 2004; lower purchase intention, Choi & Mattila 2008).
Co-producing service outcomes with AI systems also represents a social interaction (Henkel, et al., 2020; van Doorn et al., 2017), such that the responsibility for the outcome of such interactions may be attributed to either one of the actors (i.e., the AI system or the human; Jörling, Böhm, and Paluch 2019; Meuter et al. 2000). Perceived outcome responsibility has mostly been investigated when a service is co-produced between a customer and self-service (Meuter et al., 2000) or computer technology (Moon, 2003). Research has recently begun to investigate the factors that drive attribution of responsibility when a service is co-produced with service robots (Belanche et al., 2020; Jörling et al., 2019).

Meanwhile, internal service co-production of employees and AI systems has received little attention from service researchers, even though this form of service co-production opens up significant responsibility issues (Santoni de Sio & Mecacci, 2021). For example, physicians might co-produce health evaluations with AI systems (Hsu, 2017), thereby detaching themselves from psychologically owning the diagnosis. Alternatively, lawyers increasingly make use of contract review systems (Spring et al., 2022), shifting responsibility for service outcomes to the AI system. Such systems might thus lead employees to not take responsibility, facilitate socially and in some cases also economically undesirable outcomes, and potentially even cause legal problems for organizations (Semigran et al., 2016).

Relatively little is known about the mechanisms leading employees to assume less responsibility when co-producing services with AI systems. One explanation might be that unfulfilled psychosocial needs of employees when co-producing service with non-collaborative AI systems lead to diminished responsibility taking (Bradley et al., 2010; van Raaij & Pruyn, 1998). Indeed, some scholars suggest that AI system feature design can mitigate responsibility gaps when human psychosocial needs are taken into consideration and, accordingly, develop design principles for AI systems (Zerilli et al., 2019). From a consumer perspective, need fulfillment has also been identified as a driver of perceived responsibility when service is co-produced with a service robot (e.g., need for control; Jörling et al., 2019). We build on these insights and conceptualize an important role of employees' psychosocial needs in our framework that connects the collaborativeness of AI systems and employee responsibility taking. In the development of our conceptual model, we specifically draw on service encounter needs theory (SENT; Bradley et al. 2010).

5.3.1.3 Service Encounter Needs Theory

Service encounters are not only an economic transaction between two parties, but also fulfill psychosocial needs of the social agents involved (cf., Bradley et al. 2010). In turn, the fulfillment of psychosocial needs drives positive service encounter outcomes (e.g., perceiving control fosters satisfaction; Collier & Sherrell, 2010). Collaborating with smart, self-learning AI systems is a social interaction (Henkel et al., 2020; van Doorn et al., 2017); we thus extend SENT to the setting of employee-CI system collaboration and posit that the fulfillment of human needs in such encounters should foster positive service outcomes.

In SENT, Bradley et al. (2010) define a need as "a recurrent (latent) concern for a goal state, an inner force that directs behavior towards a goal and causes tension when the goal is not satisfied" (p. 232). They identify four task/utilitarian needs, which relate to the way actual tasks are co-produced and information is shared within the service encounter: the need for control, cognition, competence, and justice. These needs are particularly crucial for employees because they co-produce a service with AI systems at work. Utilitarian interests are dominant when the aim is to successfully finish a task. Therefore, we specifically focus on these four needs when we develop our hypotheses below.

5.3.2 Hypotheses Development

5.3.2.1 CI System Features and Psychosocial Need Fulfilment

The fulfillment of human psychosocial needs is essential in service co-production because it drives positive service outcomes (Bendapudi & Leone, 2003). Whereas human actors can simultaneously adapt to their counterparts' needs that are implicitly or specifically stated in service co-production (Bradley et al., 2010), state-of-the art digital AI systems do not yet have this kind of agency (van Zoelen et al., 2021). Hence, conscious AI system feature design is essential to meet human psychosocial needs (Zerilli et al., 2019). Extant research in the service and robotics field has produced rich knowledge on how features of various AI systems (e.g., anthropomorphism, interaction style, etc.) drive human responses to such systems, such as in the form of warmth (Choi et al., 2021) and control perceptions (Jörling et al., 2019), or trust in and acceptance of the technology (Maggi et al., 2021). In a financial service setting, Hildebrand and Bergner (2021) show that a conversational design of a robot advisor fosters positive firm attributions and recommendation behavior through affective trust towards the robo advisor.

Since technology design is essential in driving people's responses to human-technology collaboration, we posit that the fulfillment of psychosocial needs in service co-production equally depends on the collaborative design of service AI systems. Thus, service AI systems characterized by reciprocal strength enhancement, engagement, transparency, process control and outcome control (i.e., CI systems) should positively affect employees' task-related need fulfillment.

Control. The need for control is fulfilled when humans feel that they can "influence, manage, and master their environment and the events and outcomes that occur within it" (Bradley et al., 2010, p. 238). When in control, humans feel mastery of their circumstances or environment and do not feel controlled by external forces when co-creating service. Meuter et al. (2000) show that perceived control over a self-service terminal fosters customer satisfaction and Sowa et al. (2021) find that employees prefer AI systems over which they perceive control. Dietvorst et al. (2016) showed that the option to modify outputs (i.e., perceptions of control) increased reliance on algorithms. Moreover, Jörling et al. (2019) show that when customers are able to manually configure AI systems (e.g., adjusting functions in smart heaters or autonomous cars), their perceived responsibility for service outcomes increases. Hence, co-producing services with CI systems, that allow employees to control the processes and outcomes during service co-production, are likely to positively affect feelings of control.

Cognition. The need for cognition is met when ambiguity and uncertainty are minimized and people feel that they understand the processes and circumstances underlying service co-production (Bradley et al., 2010). For instance, individuals demand explanations to gain clarity in situations where they feel confused or bewildered, such as in case of service failure (McColl-Kennedy & Sparks, 2003). An important CI system feature in this regard is transparency, which posits that the outcomes of analyses are clearly explained. AI transparency has been shown to have positive effects on the joint collaboration (e.g., Chen et al., 2018; Lyons et al., 2016). CI systems are also designed to be engaging, which makes it easier for users to ask questions when they have a need to be better informed. Hence, CI systems should positively influence the fulfillment of the need for cognition.

Competence. When humans feel useful, efficacious and confident that they are able to fulfill all required behaviours effectively to generate the desired outcome in service co-production, their need for competence is met (Bradley et al., 2010). The feeling of competence emerges when humans have enough information through experience to judge that they are capable to perform a certain task (Bandura, 1997). Such competence stimulates the use of (self-)service technologies (Meuter at al., 2000). When co-producing a service with CI-systems, employees may develop feelings of self-efficacy as they learn that working with the system enhances their own strengths, while the feedback that they provide improves the CI system itself (i.e., reciprocal strength enhancement). Moreover, the features of process and outcome control implicitly stimulate employees to feel efficacious. For example, the final approval of service outcomes always lies with the human user (i.e., outcome control).

Justice. Finally, the need for justice in co-produced service encounters is fulfilled when humans "believe that justice has been (or is being) done" (Bradley et al. 2010, p. 249). Outcomes should be obtained through fair processes and humans' efforts should lead to a just return. In the context of algorithmic decision making, Lee et al. (2019) show that perceived fairness emerges when outcomes are explained (i.e., transparency) and users can decide over final outcomes (i.e., outcome control). Moreover, the reciprocal strength enhancement nature of CI systems ensures that user feedback to the system enhances the users' job performance. This reciprocity principle strongly links to fairness perceptions (Folger et al., 2010). Hence, we posit that CI systems should positively affect users' justice perceptions.

Based on the above insights, we hypothesize:

H1: CI systems, that are characterized by reciprocal strength enhancement, engagement, transparency, process control, and outcome control have a positive effect on the fulfillment of employees' need for (a) control, (b) cognition, (c) competence, and (d) justice.

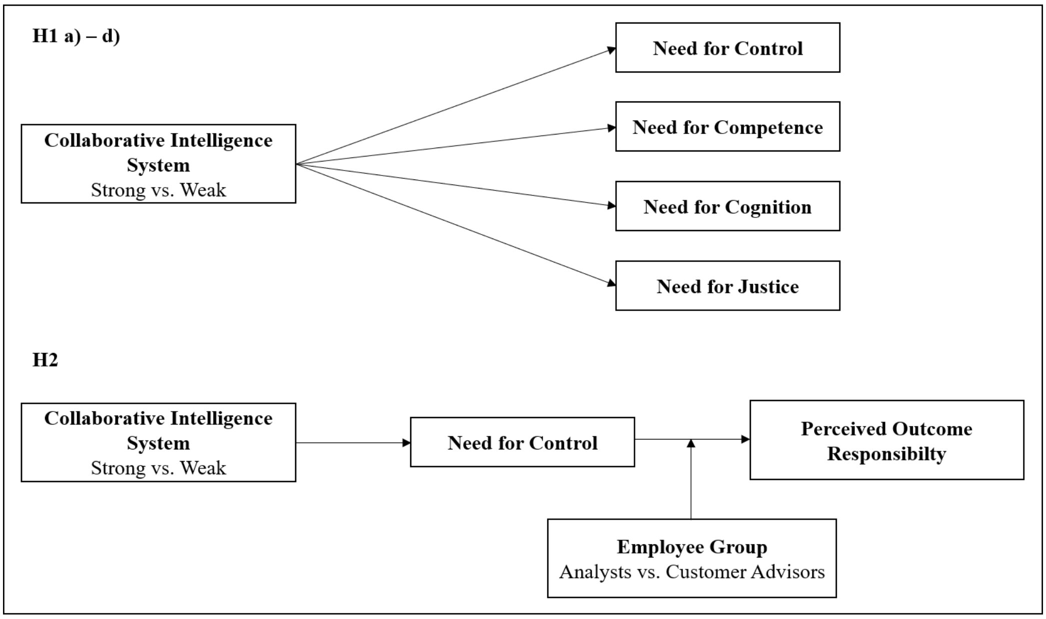
5.3.2.2 Retainment of Employee Responsibility Taking

As explained earlier, employees taking responsibility for the outcomes of services co-produced with CI systems is crucial for service firms. However, there is clear evidence that working with smart technology can diminish employees' responsibility taking or ownership of service outcomes when certain aspects of the tasks are delegated to an autonomous system (Santoni de Sio & Mecacci, 2021).

SENT suggests that positive outcomes of co-produced services, such as responsibility taking, can be explained through need fulfillment (Bradley et al., 2010). There are few studies that explore the mechanisms that explain responsibility taking in service co-production (Albrecht et al., 2017). Yet, when investigated, perceived control has been identified as a key driver of taking responsibility for or ownership of service outcomes in traditional human-to-human service co-production (van Raaij & Pruyn, 1998) and when service outcomes are co-produced with self-service technology (Reinders et al., 2008) and social robots (Jörling et al., 2019). Research further suggests that control in the form of making own choices during service co-production increases inter alia feelings of accountability for the outcome (Botti & McGill, 2011). Moreover, Santoni de Sio and Mecacci (2021) argue that perceived control is central to solving responsibility issues in human-AI collaboration. In light of this evidence, we posit that a fulfilled need for control will mediate the positive effect of CI systems on employees' perceived outcome responsibility. We thus hypothesize:

H2: The fulfillment of the need for control mediates the effect of CI systems on employee's perceived outcome responsibility.

Figure 11 depicts our conceptual model.



Note. Strong (vs. weak) collaborative intelligence systems describe CI systems that have pronounced collaborative features (i.e., reciprocal strengths enhancement, engagement, transparency, outcome control, and process control).

Figure 11: Conceptual Model

Additionally, we propose that the magnitude of need for control's mediating effect depends on contextual factors (Bradley et al. 2010). Specifically, we are interested in how CI systems' relationship to employee responsibility taking differs between employee groups. For example, extant research shows that university faculty members have a higher need for cognition than assembly workers (Cacioppo & Petty, 1982). Analogously, in a banking context, analysts that collaborate with CI systems to evaluate the credibility of a corporate customer might respond differently to the system compared to customer advisors who collaborate with CI systems to contact and counsel customers. Both the task and the job profile of these employee groups differ. As we have no formal a priori expectations regarding the pattern of any potential contingency effect, we propose, exploratively, that the strength of the mediated effect of CI systems on responsibility taking through fulfillment of the need for control differs across employee groups.

5.3.3 Experimental Design and Study Context

To test our hypotheses, we conducted two 2x2 between-subjects scenario-based experiments followed by a questionnaire aimed at two distinct employee groups in the banking sector (i.e., analysts and customer advisors). The scenarios either described an AI system working together with analysts or customer advisors on a typical task in the work context of the respective employee groups (see Appendices M and N)[8]. In the scenarios, we manipulated each of the five CI system features (i.e., reciprocal strength enhancement, engagement, transparency, process control and outcome control**)** as either strongly or weakly pronounced (i.e., strong CI system vs. weak CI system)[7]. We chose this experimental approach as scenario-based studies are particularly suitable for studying innovative technologies which are not yet widely spread, such as AI (Rijsdijk & Hultink, 2003).

The two studies are separately conducted with two different groups of employees (i.e., analysts and customer advisors) working at a corporate bank. Financial services provide a suitable context to investigate the effects of CI system design, because AI is

[8] In light of our study context in banking, specifically loan approvals for corporate customers, we questioned whether the amount of money with regards to the credit loan at stake would influence the results. Furthermore, by indicating an amount of the credit loan, we aimed to create a more realistic situation for the employees to put themselves into, thus enhancing external validity. Hence, we controlled for the amount of the loan and randomly indicated considerably higher and lower amounts (100k vs. 20mio €) which were based on our qualitative analysis and data of our partner organization. We found no effect of the loan amount.

a disruptive force in the financial sector. AI is increasingly adopted in this sector because successful financial services rely on big and unstructured data which cannot be analyzed by a single person—think about the complexities in granting credit loans (Berlucchi et al., 2016; McKinsey, 2021). Thus, employees in the banking sector are used to technology to support their daily work and need powerful analytical systems to achieve their individual goals. However, employees still need to rely on their expertise and experience in their decisions and take information into consideration which cannot be easily formalized in AI processable data (Kokina et al., 2019). For example, analysts consider their individual knowledge on the future potential of regions where corporate clients plan their projects and customer advisors weigh in their knowledge on the reliability of a customer. Moreover, as stakes are higher in corporate banking compared to private banking, the context is likely to witness increased employee-AI collaboration in the near future (DBS Bank, 2021; Kokina et al., 2019; McKinsey, 2021).

To design robust and realistic scenarios in the context of corporate banking, we followed a comprehensive approach. First, we gathered qualitative data in interviews with three analysts as well as with three customer advisors from our focal financial institution. This ensured that the scenarios reflected a typical work situation and used the right terminology. Second, to further enhance external and face validity, we discussed the scenarios and manipulations with 14 practitioners from other banking institutions. Finally, we discussed our manipulations of the CI system features with a group of nine researchers to make sure these elements are clearly described and do not conceptually overlap.

5.3.4 Participants and Procedure

To gather our samples, more than 10,000 employees of a national bank in Europe were invited to participate in the two surveys via an e-mail newsletter. Each employee group (i.e., analysts and customer advisors) received a link to the applicable survey. To encourage participation, each participant was given the opportunity to enter a lottery to win one of thirteen Amazon gift vouchers with a total value of 500 Euros. Our final sample in the analysts group consists of 185 responses (M_{age} = 46; SD = 10.02; 68% male) with over 50% having more than 16 years of work experience. We also received 124 responses of customer advisors (M_{age} = 39; SD = 10.6; 82% male) with over 50% having more than 20 years of work experience.

In the online experiment participants were asked to carefully read a scenario and picture themselves into this situation. They were then randomly assigned to either of two experimental conditions—a weakly pronounced or strongly pronounced CI system[7] —after which they answered six attention check questions on the scenario content (e.g., "*You know the parameters the AI considers in its decision making?*"). Participants who passed the attention check were forwarded to the dependent variable and mediator measures.

We mostly used established scales to measure participants' need fulfillment in the context of an internal service encounter. *Need for control* was measured using four items adapted from of Yagil and Gal (2002), *need for justice* was measured using four items adapted from Elkins and Phillips (2000), and *need for competence* was measured with four items adapted from Radel et al. (2011). Due to a lack of applicable scales in literature, we generated four new items to measure the *need for cognition* based on its definition (cf., Bradley et al., 2010). To measure *perceived outcome responsibility* we adopted three items from Botti and McGill (2011) and included one additional item based on Gosling, Denizeau and Oberlé (2006). All constructs were measured on a 7-point Likert scale.

Following the measures of our focal variables, we included a manipulation check asking participants to rate the extent to which the described AI appeared as *collaborative* on a 7-point scale ranging from *not collaborative at all* to *very collaborative*. We included a clarification of the meaning of collaborative based on prior literature (see Appendices O and P; Mattessich and Monsey 1992). We also checked participants' perception of each individual CI feature on a 7-point scale ranging from *very low* to *very high* (e.g., "*How do you rate the transparency of the describe AI?*"). Furthermore, we had participants rate the realism ("*I think the scenario is realistic.*") and complexity ("*I could easily put myself into the described scenario.*") of the scenario. Finally, we asked participants for their position within the organization, tenure, and demographics. Appendices M-Q provide an overview of all scenarios of the respective experiment conditions, included scales, and items.

5.3.5 Results

Reliability and Validity. Table 10 provides the means, standard deviations, and construct-level correlations for all constructs in both samples. The table also shows that composite reliability (CR) and factor reliability (FR) scores exceed the suggested thresholds for all constructs across datasets (Richard P. Bagozzi & Yi, 1988). Moreover, the average variance extracted (AVE) exceeds the threshold of .50 for all constructs and the square root of AVE is greater than correlations with other constructs (Fornell & Larcker, 1981). To further establish discriminant validity beyond the Fornell and Larcker criterion, we calculated heterotrait-monotrait (HTMT) ratios which do not exceed the critical value of .85 (Henseler et al., 2015). Thus, internal reliability as well as convergent and discriminant validities are established.

Analysts Sample							
	M	**SD**	**1**	**2**	**3**	**4**	**5**
1. Need for Control	3.21	2.05	**.81**	.67	.23	.75	.69
2. Need for Cognition	3.26	1.79	.65***	**.81**	.42	.63	.54
3. Need for Competence	5.24	1.61	.22***	.40***	**.83**	.35	.21
4. Need for Justice	3.83	1.93	.72***	.61***	.34***	**.95**	.68
5. Perceived Outcome Responsibility	4.35	2.04	.65***	.52***	.20***	.66***	**.89**
AVE			.81	.81	.83	.91	.79
FR			.95	.97	.95	.98	.94
CR			.94	.95	.95	.97	.94
Customer Advisor Sample							
	M	**SD**	**1**	**2**	**3**	**4**	**5**
1. Need for Control	3.50	1.93	**.88**	.82	.21	.77	.50
2. Need for Cognition	3.51	1.59	.78***	**.88**	.28	.72	.42
3. Need for Competence	5.25	1.52	.20**	.27***	**.91**	.23	.21
4. Need for Justice	3.89	1.84	.74***	.70***	.23**	**.95**	.38
5. Perceived Outcome Responsibility	4.52	1.84	.46***	.39***	.19**	.35***	**.82**
AVE			.79	.79	.83	.90	.68
FR			.94	.95	.95	.97	.89
CR			.93	.95	.95	.97	.89

Note. AVE = average variance extracted; FR = factor reliability; CR = composite reliability; Numbers on the diagonal in bold present the square root of the AVE. Numbers below the diagonal present the correlations between constructs; numbers above the diagonal present the HTMT (heterotrait-monotrait) ratios; *** p < .00; ** p <.05.

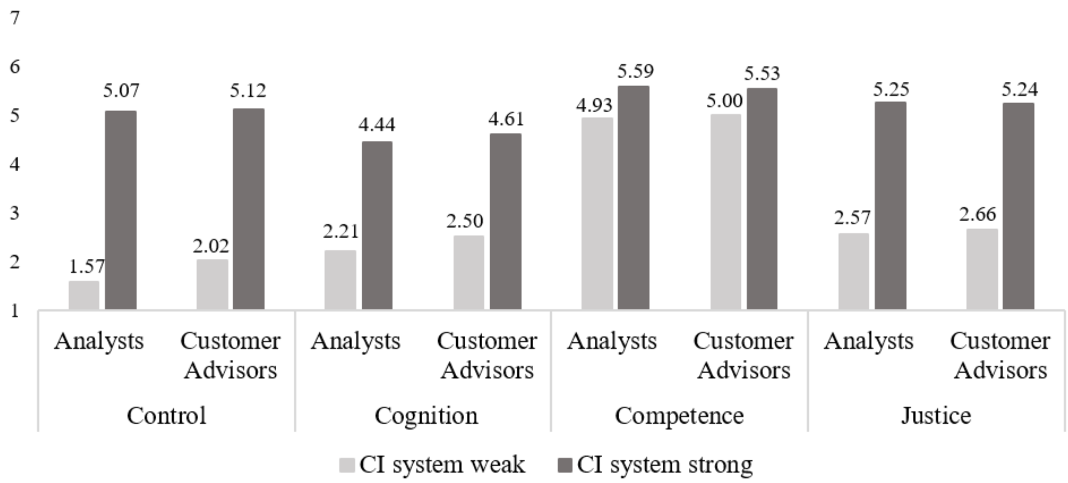
Table 10: Descriptive Descriptives, Intercorrelations, Reliability and Validity Scores

Manipulation, Realism, and Complexity Checks. We carried out an analysis of variance (ANOVA) for the CI manipulation in both samples. Results revealed a significant difference in participants' perception of the collaborativeness of the AI between the experimental conditions (analysts: $M_{\text{CI\_weak}} = 1.85$, $M_{\text{CI\_strong}} = 5.13$, $F_{(1, 184)} = 374.34$, $p < .000$; customer advisor: $M_{\text{CI\_weak}} = 2.02$, $M_{\text{CI\_strong}} = 5.08$, $F_{(1, 123)} = 152.20$, $p < .000$). Also the perceptions of all five, averaged, CI features significantly differed between conditions (analysts: $M_{\text{CI\_weak}} = 1.79$, $M_{\text{CI\_strong}} = 4.76$, $F_{(1, 184)} =$

409.30, $p < .000$; customer advisors: $M_{\text{CI\_weak}} = 2.11$, $M_{\text{CI\_strong}} = 5.05$, $F_{(1, 123)} = 228.77$, $p < .000$). Means for the realism and complexity checks (RC; CC) across study conditions rated well above the scale mid-point in both samples, showing that the respondents found all scenarios to be realistic and were able to put themselves into the situation even though the scenario described a futuristic work situation (analysts: $M_{RC} = 4.50$, $M_{CC} = 4.85$; customer advisor: $M_{RC} = 4.33$, $M_{CC} = 4.86$).

Effects of CI system on Employees' Need Fulfillment. To test the effects of CI on employees' need fulfillment we conducted a multivariate analysis of covariance (MANCOVA) with each sample controlling for age, gender, tenure, and credit loan amount. The assumption of equality of variance and covariance was rejected based on a significant Box' M for the analysts but not for the customer advisor sample. Hence, we turned to Wilk's Lamda for the customer advisor sample. The results showed significant main effects of CI system on employees' need fulfillment (analysts: Pillai's Trace = .75, $F_{(4, 177)} = 129.20$, $p <. 000$; customer advisors: Wilk's Lamda = .33, $F_{(4, 117)} = 59.45$, $p <. 000$). In the analysts sample, all between-subject tests showed that a strong CI system was related to greater fulfillment of the needs for control ($M_{\text{CI\_weak}} = 1.57$, $M_{\text{CI\_strong}} = 5.07$, $F_{(1, 184)} = 471.68$, $p < .000$), cognition ($M_{\text{CI\_weak}} = 2.21$, $M_{\text{CI\_strong}} = 4.44$, $F_{(1, 184)} = 121.00$, $p < .000$), competence ($M_{\text{CI\_weak}} = 4.93$, $M_{\text{CI\_strong}} = 5.59$, $F_{(1, 184)} = 8.14$, $p = .005$), and justice ($M_{\text{CI\_weak}} = 2.57$, $M_{\text{CI\_strong}} = 5.25$, $F_{(1, 184)} = 171.16$, $p < .000$).

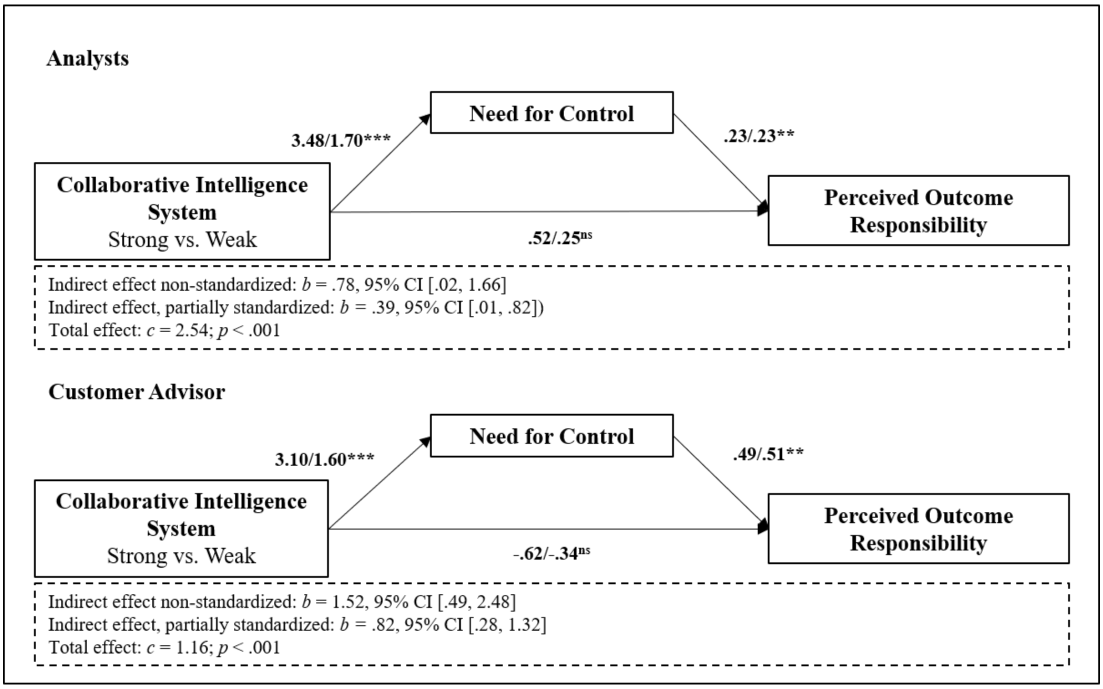
In the customer advisors sample, the post hoc test showed that a strong CI system was related to greater fulfillment of the needs for control ($M_{\text{CI\_weak}} = 2.02$, $M_{\text{CI\_strong}} = 5.11$, $F_{(1, 123)} = 213.98$, $p < .000$), cognition ($M_{\text{CI\_weak}} = 2.50$, $M_{\text{CI\_strong}} = 4.61$, $F_{(1, 123)} =102.23$, $p < .000$), justice ($M_{\text{CI\_waek}} = 2.66$, $M_{\text{CI\_strong}} = 5.24$, $F_{(1, 123)} = 117.16$, $p < .000$), and, albeit with borderline significance, competence ($M_{\text{CI\_weak}} = 5.00$, $M_{\text{CI\_strong}} = 5.53$ $F_{(1, 123))} = 3.81$, $p = .053$). Our results thus support H1a-H1d, though H1c has marginal support in the customer advisors sample. Figure 12 depicts for both samples the mean differences in the fulfillment of each need in the strong and weak CI system condition.



Note. Strong (vs. weak) collaborative intelligence systems describe CI systems that have pronounced collaborative features (i.e., reciprocal strengths enhancement, engagement, transparency, outcome control, and process control).

Figure 12: Mean Differences in the Fulfillment of each Need for both Employee Groups

Mediating Role of Need for Control. To test our second hypothesis, we conducted regression-based mediation analyses using Model 4 in the PROCESS macro in SPSS27 (Hayes 2018) with degree of CI as the independent variable, the fulfillment of need for control as the mediator variable and perceived outcome responsibility as the dependent variable. Next to including age, gender, tenure, and credit loan amount as covariates, we modelled the need for competence, cognition, and justice as alternative mediators as to control for their potential effects. We employed 5,000 bootstrap samples and 95% bias-corrected confidence intervals. As recommended by Hayes (2018) for dichotomous independent variables in mediation analyses, we report non-standardized coefficients as well as the partially standardized coefficients (i.e., *part_std*: results when standardizing the dependent but not the independent variable). In both samples, results reveal a significant indirect effect of the degree of CI system on perceived outcome responsibility, mediated by the need for control (analysts: b = .78, 95% CI [.02, 1.66], b_{part_std} = .39, 95% CI [.01, .82]); customer advisor: b = 1.52, 95% CI [.49, 2.48], b_{part_std} = .82, 95% CI [.28, 1.32]). In both samples, the results reveal a full mediation effect because the direct effect, accounting for the mediating effect of control is not significant in the analyst sample (direct effect: c' = .52, $c'_{\text{part\_std}}$ = .25, p = .22) nor in the customer advisor sample (direct effect: c' = -.62, $c'_{\text{part\_std}}$ = -.34, p = .24). Figure 13 reports all effects.



Note. Coefficients are depicted as non-standardized/partially standardized. Strong (vs. weak) collaborative intelligence systems describe CI systems that have pronounced collaborative features (i.e., reciprocal strengths enhancement, engagement, transparency, outcome control, and process control).

Figure 13: Effect Sizes of Mediation Analyses

We conducted several post hoc analyses where we explored whether the other psychosocial needs would also mediate between the degree of CI and responsibility taking. These explorations revealed a positive significant mediating effect of need for justice for analysts (b = 1.04, 95% CI [.46, 1.58]; b_{part_std} = .51, 95% CI [.23, .77]) while no such effect can be found in the customer advisor group (b = .04, 95% CI [-.57, .83]; b_{part_std} = .02, 95% CI [-.32, .45]). This indicates that when considering different job profiles, next to the need for control other needs might be relevant to explain the relationship of CI systems and responsibility taking. We further discuss the findings on the job profiles, and their implications, in the general discussion section.

5.4 General Discussion

This research identifies what CI system features foster service co-production and how employee responsibility taking can be retained when service outcomes are co-produced with CI systems. To this end, it first systematically develops the concept of CI systems in the context of service co-production, identifies five relevant design features (i.e., reciprocal strength enhancement, engagement, transparency, process control, and outcome control) and demarcates the newly developed framework from related concepts. Then, using two experimental studies with different employee groups in a financial service context, this research shows that CI systems have a positive effect on the fulfillment of employees' psychosocial needs. Specifically need for control takes an important role, because the fulfillment of this need subsequently drives the positive effect of pronounced CI system features on employee responsibility taking. Finally, we demonstrate that the mediating mechanism differs between employee groups, because for analysts (but not for customer advisors) also the fulfillment of the need for justice is a potent mediator in explaining the relationship between CI and responsibility taking.

5.4.1 Theoretical Implications

With our research, we make four main contributions to literature. First, by delineating the concept of a CI system in service co-production we contribute to the emerging literature on human-AI collaboration in service settings (e.g., Paluch et al., 2022; Sowa et al., 2021). While a stream of literature considers on which tasks AI can augment humans to create an ideal service mix (e.g., Huang & Rust, 2022), we add to this by uncovering the AI system features that benefit collaboration in service co-production. Moreover, in contrast to lively discussions on customers and their AI adoption (e.g., Amelia et al., 2022) and despite repeated calls (Ostrom et al., 2015; Ostrom et al., 2021; Xiao & Kumar, 2021), insights on how employees deal with AI systems in their daily work routine have been scant.

Second, existing employee-AI collaboration studies mostly focus on outcomes on the firm level (e.g., Wilson & Daugherty, 2018) or the dyadic level (i.e., the quality of the joint decisions made; Dellermann et al. 2019b). This work considers the individual level and, by focusing on employee responsibility, identifies a concept that may precede the quality of joint decision making, and the dyadic- and firm-level consequences. We show how CI systems should be designed to stimulate employee responsibility taking, i.e., by taking into account the five design features. With this effort we also contribute to the emerging discussion of employee engagement (Kumar & Pansari, 2016) and meaningful work (Smids et al., 2020) in the age of AI. If AI systems are designed in a collaborative manner (i.e., pronounced CI system features), it may be possible to increase firm efficiency while simultaneously maintaining employee well-being and a sense of duty and responsibility.

Third, the findings of our empirical study contribute to prior work on the mechanisms of responsibility taking in automated service settings (Belanche et al., 2020;

Jörling et al., 2019) and SENT (Bradley et al., 2010) in two main ways. To start, thus far, SENT has mainly been applied to human-to-human service encounters. We extend this theory to the emerging context of human-AI service co-production and show that strong CI systems have a positive effect on all four utilitarian employee needs we considered. In addition, our research finds that, across two samples of employees with different job profiles, the need for control mediates the effect of strongly pronounced CI system features on responsibility taking. We thus show that the need for control is also relevant to explain responsibility taking in employee-CI system service co-production.

Finally, by contrasting the effects in our conceptual model for analysts and customer advisors, we identify job profiles as an important contextual factor that determines which needs are relevant to foster responsibility taking in technology-infused service encounters. These profiles are readily controllable by managers, allowing for direct facilitation options for resource allocation to achieve successful CI system implementation. This contributes to a stream of literature that has concentrated on identifying individual differences and task characteristics as contingency factors in technology acceptance and use (e.g., Blut et al., 2016; Brown et al., 2010; Park et al., 2014). Specifically, our results demonstrate that employees with different job profiles respond differently to the same CI system, indicated by siginificantly different total effect sizes (total effects: analysts = 2.54, 95% CI [2.07, 3.00] vs. customer advisors = 1.16, 95% CI [.52, 1.87]) and other needs driving the effect of CI systems on responsibility taking. CI system design might have a greater relevance to the responsibility taking of analysts because their work results and success are much more dependent on AI systems compared to customer advisors. The well-being of the latter group may also be partially defined by maintaining strong customer relationships, highlighting not only the utilitarian, but also the emotional aspects of their work. Still, the results for both groups show that CI systems enable these employees to exercise more control over their work. Moreover, for analysts' responsibility taking was also connected to a fulfilled need for justice. Perhaps this can be explained by the fact that analysts deciding on credit loans face complex decisions that they cannot make more transparent themselves, but a CI system could help by combining many data points and offering advice. This may make analysts feel that they took a "just" decision for which they want to take responsibility. In contrast, customer advisors have much more leeway to reduce uncertainty and complexity in product selection through extensive talks with customers. While a CI system may still enhance their feelings of justice, being better informed on the interests of the customer may be a more important source.

5.4.2 Managerial Implications

The cornerstone of the fifth industrial revolution is collaboration of humans and AI-enabled systems (Noble et al., 2022) and in a recent study 70% of practitioners see AI systems as collaborative service tools for their employees rather than substitutes (PwC, 2019). Moreover, customers still demand human service employees in decision making processes (Yalcin et al., 2022). Hence, it is important to understand how successful employee-AI collaboration in service co-production can be managed, including challenges such as employees' responsibility taking. Our work offers two main implications for service managers to address these issues.

First, we provide service managers and designers with a blueprint for CI system design that fulfills employee needs. We show that considering employee needs is an important step to safeguard employee responsibility taking. Service managers and requirement engineers may use the five CI system features that we identified as a blueprint to design internal service processes based on human-AI collaboration. For example, practitioners could identify *where* the collaboration process benefits from input from the employee and could program CI systems to allow *process control* (e.g., ask the user's opinion through a chat function or speech interface) at these crossroads. Similarly, *engaging* the employee (e.g., proactively showing the potential consequences of good vs. erroneous decisions) and providing *transparency* (e.g., an algorithm sharing its priors with an employee) might as well only make sense at certain crossroads depending on the internal process and should thus be identified a priori.

The CI system features also help managers think about *how* collaboration in service co-production can be enhanced. For example, practitioners can identify how the features of *transparency* and *engagement* should be presented to different employees and in different tasks. In some cases, a visual explanation of analysis results might be preferable over a textual while other situations benefit from a vocal explanation. Depending on the type of process and work environment, *engagement* of the CI system could be designed as push notifications, vocal address, or a simple highlighted notification button. With regard to *outcome control,* managers could consider boundaries which restrict employees to overrule CI system decisions or, alternatively, define a threshold above which changes to the CI advice have to be confirmed by other decision makers.

When making design choices based on the CI-principles, managers could also consider individual employee preferences and provide a variety of setting options. To identify preferences and enhance the CI design-user fit for internal processes, managers and requirement engineers could consider system development in co-design with users (Trischler et al., 2018). Here, users are trained on the CI-principles and can consequently give their own expert insights *where* and *how* collaboration between the user and the system could be fostered.

Second, total effect comparison of the two studies shows that the effect of CI systems on responsibility taking is greater for analysts than for customer advisors. Since CI system design is costly, managers should thoroughly consider for which employee groups and tasks CI systems are relevant. Our findings also highlight that there are differences between employee groups with regards to which needs, or their fulfillment, mainly contribute to employee responsibility taking. In addition to the need of control, we found that a fulfilled need for justice also fosters responsibility taking for analysts but not for customer advisors. When introducing CI systems, managers should thus consider the context of the service the CI system co-produces with employees and anticipate what needs might be most important to which employee groups and make sure that the CI system design fulfills these needs sufficiently. Additionally, it would be beneficial to train CI system designers to increase their awareness of which functionalities and design features affect user needs and how they might be best implemented in such systems.

5.4.3 Limitations

We acknowledge several limitations of our research. First, we conceptualized our CI system with great diligence based on a literature review and a follow-up qualitative study. However, we acknowledge that literature searches with different inclusion criteria and a less restrictive focus on service co-production might have put forth additional or differently defined CI system features that we might have missed through our approach.

Second, scenario-based experiments are common in research that focuses on cutting-edge technology that lacks publicly available prototypes (e.g., Choi et al., 2021; Schepers et al., 2022). However, such setups may also raise external validity concerns. In our case, despite the fact that we took great care to create realistic scenarios, it might well be that long-term interaction with CI systems would produce different effects on employee need fulfillment and responsibility taking. For example, positive effects might occur because of a novelty effect and diminish over time. Alternatively, in reality CI systems may fail to co-produce service as expected and employees might lose patience or trust or stop their collaboration with the system entirely (Dietvorst et al., 2015). We thus urge scholars to consider long-term field research designs with actual CI systems in various contexts in the future.

Third, extant research shows that employees vary in their perceptions of technology based on individual characteristics such as technology readiness (Parasuraman & Colby, 2015) or fear of job loss (McClure, 2018; Vorobeva et al., 2022). Such individuals might reject working with AI systems, regardless of the design, and would struggle to take responsibility for an outcome co-produced with a CI system. Future research might thus consider these individual differences.

5.4.4 Future Research Agenda

Our research is the first to consider system design features that foster employee-AI collaboration when co-producing service outcomes. The newly developed CI system concept opens manifold avenues for future research. To move CI systems research in the services field forward, we next outline future research opportunities according to four foci and propose concrete future research questions in Table 11.

First, future research could further develop our CI system conceptually. For example, we propose a holistic yet multi-dimensional view on the CI system concept, where features may have slight overlap or even complement each other. However, extant research suggests that CI system features could also potentially negate each other. For example, if a CI system engages users autonomously in the process of collaboration it might lead to higher CI system agency perceptions which might decrease feelings of control (Zafari & Koeszegi, 2021). Future research might consider how different CI system features relate to each other.

Second, future research could further empirically investigate the downstream consequences of using CI systems. For example, we suggest to consider additional focal variables (e.g., meaning of work) and alternative mechanisms (e.g., positive or negative emotions) to further detail the effects of CI systems on various employee outcomes. Because we focused exclusively on the financial sector, we also suggest to investigate how the relevance of different CI systems features differs between service co-production contexts.

Third, service researchers could consider which additional psychosocial needs might drive the positive effects of CI systems on employee outcomes. In our work, we built on the task/utilitarian needs outlined in SENT (Bradley et al., 2010), but the theory also accounts for socioemotional needs (e.g., needs for power or pleasing relations). We consider these less fitting in our context because in contrast to social robots, CI systems likely are lower in social presence. However, when collaborating with CI systems over a longer period of time, employees might build a relationship with the systems (Schweitzer et al., 2019) and socioemotional needs such as pleasing relations might become relevant. Also, we have speculated that some employees may benefit from socioemotional connections to customers to fulfill their needs in utilitarian tasks. In sum, clarifying the relationships between the different needs in SENT and their connection to CI systems and other actors in the service environment is a rich area for further research.

Finally, future research could focus on ethical considerations when firms introduce CI systems. For example, there might be long-term consequences for employees that work intensely with CI systems. Think about employees who, due to their dependence on a CI system, might interact less with human colleagues. This could negatively affect their need for social belongingness or, ultimately, well-being.

In closing, we feel that CI systems are an intriguing technological development in modern service firms. This development brings with it a host of unanswered research questions and we hope that our work can spark researchers' interest to help further develop this area.

Focus	Example Future Research Questions
Further conceptual development of CI system concept	▪ Are all CI system features equally relevant? ▪ What could be additional relevant features depending on the collaboration context? ▪ What could be potential unintended interaction effects between the CI system features? For example, if a CI system is autonomously engaging it might lead to higher CI system agency perceptions which in turn can decrease feelings of control (Zafari & Koeszegi, 2021) despite clear control-related features. ▪ What could be unintended negative effects of the CI system features depending on the context? For example, process control might lead to false decision making or even fraudulent behavior when employees change wrong parameters in a decision-making process.
Further empirical evaluations of CI systems concept	▪ Which individual CI system feature drives the positive effects on employee outcomes in different contexts? ▪ Do CI systems have a positive effect on other employee outcomes such as meaning of work, positive affect, and work performance? ▪ Will the positive effects of CI systems in employee outcomes prevail over time? ▪ Which other individual and contextual factors moderate the positive effects of CI systems on employee outcomes (e.g., responsibility taking)? ▪ Which effect does the collaboration of employees and CI systems have (over time) on outcomes on team- and firm-level? ▪ Do CI systems always foster responsibility taking? For example, if CI systems would be introduced in a team setting, would responsibility taking be enhanced or foster responsibility diffusion? ▪ What other theories, next to SENT, might explain the positive effects of CI systems on employee outcomes (e.g., the effects could be explained through positive emotions based on appraisal theory)?
Psychosocial needs	▪ How do the needs that drive positive effects of CI systems on employee outcomes differ between employee groups? How would this affect CI system design? ▪ What other needs might be relevant to explain employee outcomes when working with CI systems (e.g., socio emotional needs, Bradley et al., 2010)?
Ethical considerations	▪ What are important ethical considerations when introducing CI systems for service co-production with employees? ▪ What are long-term consequences for employees of intense collaboration with CI systems? For example, would collaboration with colleagues and sharing of tacit knowledge be negatively affected over time?

Table 11: Future Research Agenda

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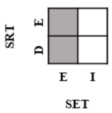
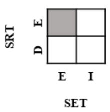
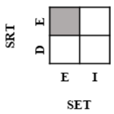
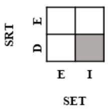
6. General Discussion

6.1 Theoretical Implications

By investigating different HRSI types through leveraging a variety of research approaches, this thesis offers several theoretical implications for the service and robotics literature. The included research projects advance HRSI-related knowledge in several ways along three overarching contributions: (1) HRSI knowledge consolidation, (2) HRSI theory or concept development, and (3) empirical HRSI concept evaluation. An overview of the contributions that each chapter of the current thesis puts forth is depicted in Table 12.

	HRSI Knowledge Consolidation	HRSI Theory/Concept Development	Empirical HRSI Concept Evaluation
Chapter 2 		▪ Service Encounter 1.0 Theory Evaluation Scheme ▪ Role theory 2.0	
Chapter 3 	▪ Overview of empirical HRSI research across scientific disciplines along various dimensions	▪ D^3 framework to structure HRSI literature and derive practical implications for service robot implementation into the frontline	
Chapter 4 	▪ Overview of knowledge of service robots' impact on vulnerable consumers' well-being	▪ Typology of service robot roles for transformative service ▪ Framework of robotic transformative service research	
Chapter 5 	▪ Overview of employee–AI collaboration concepts	▪ Conceptualization of CI systems ▪ Application of SENT in the HRSI context	▪ Knowledge generation on the effect of CI systems on employee need fulfillment and responsibility taking

Note. The images under each chapter in the first column depict which HRSI (Human-Robot Service Interaction) type each chapter focuses on; y-axis: SRT = Service Robot Type, D = Digital, E = Embodied; x-axis: SET = Service Encounter Type, E = External, I = Internal, SENT = Service Encounter Needs Theory.

Table 12: Overview of the Thesis's Contributions

6.1.1 HRSI Knowledge Consolidation

Chapters 3, 4, and 5 contribute to service literature by consolidating existing HRSI knowledge related to external service encounters with embodied robots (Chapters 3 and 4) and internal encounters with digital robots (Chapter 5). Consolidating the literature related to an emerging, interdisciplinary research stream helps researchers and practitioners gain a rapid and fundamental overview of extant knowledge and gaps in literature. Hence, it facilitates new knowledge generation by supporting scholars in positioning their research and avoiding duplicate efforts (Lim et al., 2022).

First, the fast improvements in AI-enabled service robots and growing application opportunities have sparked service scholars' research interest in recent years, leading to a surge of HRSI studies in the field. However, in the past, other disciplines, such as robotics and information systems, have already produced a great number of studies that can provide valuable insights for service research. This wealth of knowledge calls for a comprehensive review and systematic knowledge consolidation through a service research lens. Through screening over 13,500 research articles, Chapter 3 identifies 199 research articles that empirically study different phenomena in the context of HRSI and, thus, can provide important implications for service researchers and managers for the successful integration of embodied service robots in external service encounters. This chapter provides a comprehensive, general overview of extant, transdisciplinary empirical HRSI research along several dimensions (e.g., study characteristics, robot type, focal variables, and key insights) and delineates knowledge gaps.

Second, Chapter 4 identifies well-being-relevant studies on robot interactions for two vulnerable consumer groups that have been affected the most by social isolation because of the COVID-19 pandemic (i.e., children and older adults). In doing so, it provides a comprehensive overview of what is known and, crucially, what is not known about embodied service robots' transformative potential, barriers to exploiting this potential, and the effects interactions with embodied social robots have on consumers' eudaimonic well-being. Third, by systematically conceptualizing the construct of CI systems, Chapter 5 provides a systematic overview of the literature on employee–AI collaboration (i.e., service co-production in internal service encounters) and concepts related to the CI system concept (e.g., hybrid intelligence; Dellermann et al., 2019).

In summary, the present thesis provides scholars and managers with a directory of extant HRSI research related to interactions between embodied service robots and customers in external service encounters in general (cf., Appendix E), the transformative potential of embodied service robots when interacting with vulnerable consumers in external service encounters (cf., Table 6), and employee collaboration with digital service robots in internal service encounters (cf., Tables 7 & 9).

6.1.2 HRSI Theory or Concept Development

Theory assessment and conceptual advancements are crucial to knowledge development (Zaltman, 1983). Theory revisions avoid knowledge saturation, and conceptual work provides new ideas and justifies empirical studies by integrating knowledge and validating what is known (Yadav, 2010; Zaltman, 1983). Such efforts are especially crucial to move emerging fields, such as HRSI, forward (De Keyser & Kunz, 2022; Lim et al., 2022). For example, the AI job replacement theory newly developed by Huang and Rust in 2018 has been very impactful (e.g., Google Scholar citations Oct 2022: 1375) and has been used as a basis for many empirical papers already (e.g., Schepers et al., 2022). All chapters of the present thesis contribute to literature through HRSI theory or concept development in different ways according to MacInnis' (2011) framework of conceptual contributions, as detailed below.

First, by *identifying* theoretical boundary conditions of traditional service encounter theories when employed in the context of HRSI, Chapter 2 develops a novel theory evaluation scheme. In doing so, it answers the call to investigate and adapt standing service encounter theories when applied in the context of HRSI (Bock et al., 2020). Researchers can leverage the identified contextual (i.e., servicescape and service interface) and individual factors (i.e., customer skills and attitudes) that affect the temporal and spatial theoretical assumptions to develop new and adapt existing theories to explain phenomena within service encounter interactions with embodied and digital service robots. Additionally, the conceptualized theory evaluation schema is exemplarily used with role theory, which gives researchers an overview of which role theory premises need to be adapted when employed for HRSI research.

Second, by *summarizing* extant HRSI literature through the newly developed structuring D^3 framework (design, delegate, deploy), Chapter 3 synthesizes extant knowledge on customer interactions with embodied service robots taking on different service roles across scientific disciplines. Moreover, it utilizes the framework to derive detailed practical implications for successful customer–service robot interactions and to point out existing gaps in literature. By doing so, Chapter 3 answers the calls for more cross-disciplinary perspective taking and an assessment of the roles and impact of embodied robots in service provision (Lu et al., 2020). Furthermore, the D^3 framework serves scholars and practitioners to structure and design future research or define strategies for including social robots in different services.

Third, by *integrating* knowledge from service research, social robotics, social psychology, and medicine, Chapter 4 develops a typology of four embodied service robots (i.e., entertainer, social enabler, mentor, and friend) equipped to advance vulnerable consumers' (i.e., children and older adults) well-being depending on the state of social isolation (i.e., objective or subjective) and well-being focus (i.e., hedonic or eudaimonic). Moreover, it advances an integrative framework of robotic transformative service and provides detailed avenues for future research. This thesis thus pioneers the founding of an interdisciplinary research stream on well-being-directed research of HRSI—robotic transformative service research (RTSR)—which has already inspired further studies (e.g., Willems et al., 2022).

Fourth, Chapter 5 systematically *delineates* the concept of CI systems from extant research in different fields and shows how the new concept relates to other concepts around it. The CI system concept provides clear features of digital service robots that foster service co-production with employees in internal service encounters (i.e., reciprocal strength enhancement, engagement, transparency, process, and outcome control). This concept provides scholars with a new approach for studying interactions between employees and digital service robots through a service co-production perspective. Moreover, by applying service encounter needs theory (SENT) in the context of HRSI, the present thesis answers the call to investigate how standing theories can be applied to explain phenomena in AI-enabled service interactions (Bock et al., 2019). Thus, Chapter 5 helps better understand the phenomenon of employee collaboration with digital service robots and lays the foundation for further theorization of HRSI within organizations.

6.1.3 Empirical HRSI Concept Evaluation

Finally, Chapter 5 empirically investigates service co-production of employees and digital, collaborative service robots (i.e., CI systems) in internal service encounters by conducting two empirical studies. First, the CI systems concept is further developed and validated based on a qualitative study that includes semi-structured interviews with 14 practitioners. Second, two experimental studies with different employee groups in a financial service context investigate how working with CI systems leads to positive employee outcomes, such as responsibility taking. In doing so, the present thesis responds to calls for empirical studies on employee interactions with service robots to shed light on the antecedents, mechanisms, and outcomes of successful employee–service robot collaboration (De Keyser & Kunz, 2022; Ostrom et al., 2021). Drawing on SENT (Bradley et al., 2010), the results show that CI systems with pronounced collaborative features fulfill different employee psychosocial needs. Moreover, the findings indicate that the fulfillment of the need for control and justice mediates the positive effect of CI systems on employee responsibility taking and that the relevance of these two needs with regard to responsibility taking differs between employee groups. This thesis thus expands knowledge on service co-production about collaborations of employees and digital service robots in internal service encounters.

6.2 Managerial Implications

This thesis offers important insights for managers regarding the introduction of different service robot types into external and internal service encounters.

First, service managers and robot designers should be made aware of the effects of different embodied robot types on customer outcomes and decide accordingly when and where to deploy them. Chapter 3 provides a comprehensive overview of the extant HRSI knowledge about customer interactions with different embodied service robots and derives implications for how to design, which tasks to delegate and where to deploy service robots. For example, managers are advised to be cautious about designing service robots too anthropomorphic and robots should be deployed in accessible and quiet areas; delegating unpleasant tasks to service robots (e.g., picking up trash) and in potentially embarrassing service encounters (e.g., buying products for delicate medical conditions) is advised while human service providers are still preferred over current service robots in highly interpersonal service tasks, such as geriatric care. Moreover, Chapter 4 of the present thesis introduces four types of embodied service robots (i.e., entertainer, social enabler, mentor, and friend) that can enhance vulnerable consumer well-being. The chapter shows managers what types of service robots should be deployed in different contexts and which design features enhance hedonic or eudaimonic well-being considering vulnerable consumer needs. In summary, the manifold insights Chapters 3 and 4 put forth can serve managers as a roadmap for when, where, and how to introduce embodied service robots in external service encounters in different service contexts.

Second, the current thesis provides managers with insights into employee and digital robot interactions in internal service encounters. The collaboration of human employees and service robots marks the cornerstone of the fifth industrial revolution, and organizations must manage these collaborations to stay competitive (Noble et al., 2022). Although employee–robot collaboration promises efficiency gains, there are also potential downsides when employee needs are neglected (Zerilli et al., 2019). The results of Chapter 5 of this thesis show that collaborative digital service robot design (i.e., CI systems that have features of reciprocal strength enhancement, engagement, transparency, process control, and outcome control) fulfills relevant psychosocial employee needs (i.e., need for control, cognition, competence, and justice) in internal service encounters. Moreover, they show that the fulfillment of needs for control and justice mediates the positive effect of CI systems on employee responsibility taking. This mediation effect differs between employee groups. Hence, it is important to increase robot designers' and managers' awareness of which functionalities and design features affect users' needs, along with how they might best be implemented. Moreover, managers should be trained to sensitize employees to responsibility taking and explain to them, for example, what control mechanism they have when co-producing service outcomes with digital service robots to foster need fulfillment. Managers should also be aware of the varying needs between employee groups and task types and should identify these needs a priori to adapt service robot design and training measures for employees to target these particular needs.

6.3 Limitations and Future Research

Although the present thesis offers manifold insights related to HRSI in external and internal service encounters with different service robot types, they are not without limitations which can open avenues for future research.

First, the scope of this thesis does not include interactions between employees and embodied service robots in internal service encounters. Future research should consider this HRSI type as embodied service robots are increasingly introduced in the marketplace (Research Nester, 2022), acting not only as service providers for customers but, also as robotic colleagues and internal service providers for employees as well. For example, robotic colleagues support staff in elderly care by reminding patients to take their medicine (Čaić et al., 2018) or by taking on promotional tasks (De Gauquier et al., 2021). However, embodied service robots in particular come with challenges for employees. While they free employees from certain tasks, they do not yet operate on their own and need to be placed, charged, and observed during service provision, leading to additional tasks for the service employees (Paluch et al., 2022). Still, the employee perspective when working side by side with embodied service robots has been neglected thus far (Ostrom et al., 2021), and research calls for an investigation of conditions that foster collaboration. Paluch et al. (2022) and Willems et al. (2022) provide the first promising findings on employee expectations and willingness to work with embodied service robots. Yet, future research could investigate this HRSI type in more detail and shed light on what individual employee characteristics (e.g., personal innovativeness), robot design aspects (e.g., human-likeness), and contextual factors (e.g., task type, robot placement) influence employee-embodied service robot interactions.

Second, the present thesis focuses on dyadic interactions among the different HRSI types. However, these interactions do not all occur in isolation. For example, when customers interact with embodied service robots in hotels, there is most likely also human staff who, for example, will introduce the customer to the robot in a certain way. Future research should consider this service triad (Odekerken-Schröder et al., 2022) and further investigate how and when service robots, employees, and customers can jointly co-produce service outcomes. Moreover, the present thesis analyses HRSI on an individual level, neglecting the implications of service robot implementations for teams, service organizations, and ecosystems, as well as society in general. For example, future research could take a more global view and investigate how the introduction of service robots changes the nature of work and service provision as a whole, for example, in terms of dehumanization as suggested by Subramony et al. (2018).

Third, the conceptually developed RTSR framework (Chapter 4) and the CI system concept (Chapter 5) require additional empirical validation. Although both frameworks are derived based on evidence from empirical studies, the proposed effects of the transformative potential of each robot type in relation to vulnerable consumer well-being should be validated in empirical studies. Future research should also consider additional boundary factors, such as individual robot anxiety (Tatsuya Nomura et al., 2008) or perceptions of social implications of service robot deployment (McLeay et al., 2021). Moreover, even though Chapter 5 empirically investigates the effects of CI system design on employee outcomes, it leverages scenario-based experiments. This research design has limitations in relation to external validity. Hence, the effect of CI-system design should be further validated in additional empirical, ideally longitudinal field studies and with different employee groups in different contexts in the future. Moreover, future research should consider additional employee outcomes, such as employees' general willingness to collaborate with and trust in CI systems. It would also be interesting to understand if employees would follow CI system recommendations or if a collaborative design could diminish algorithm anxiety compared with non-collaborative digital service robots (Dietvorst et al., 2019). These insights would provide additional implications on the success factors for service co-production of employees and service robots within organizations.

Fourth, future research could take a particular focus on the dark side of service robot implementation, along with the ethical issues that emerge with it, and derive implications for customers, service firms, and policy makers. Although extant papers, including Chapters 3 and 4 of this thesis have already named ethical questions in relation to the implementation of different service robot types (e.g., Čaić et al., 2019), there is still considerable room for ethical discussions in relation to HRSI in the service domain (Belk, 2021). For example, Belk (2021) discusses five ethical issues in service robotics and AI (i.e., ubiquitous surveillance, social engineering, military robots, sex robots, and transhumanism) that already present ethical issues in practice and will demand additional consideration as the technology further develops. Service researchers could, for example, investigate what privacy issues the introduction of embodied service robots in retail raises, how service firms can protect customer privacy and what policies should be put into place. Similarly, service robots collaborating with employees could open up privacy and surveillance issues for employees that need to be addressed. To resolve social and ethical issues, a potential solution could lie in consequent co-design measures with all affected stakeholders in the developmental and implementation phase of service robots, however empirical insights with this particular focus are scant in service research.

Finally, the results and derived conclusions of this thesis are temporally bound. New developments in AI and robotics are announced and introduced in the market at a rapid speed, which has profound implications for service robot capabilities and, in turn, on HRSI. For example, since early 2020, when the first research project of this thesis was published, the global COVID-19 pandemic was beginning to emerge, creating additional use cases for service robots (Getson & Neja, 2021) and advancements in AI and mechanical engineering enable service robots to interact and express emotions that are more and more human-like (Huang & Rust, 2018). In response, publications related to HRSI have risen tremendously in 2021 (cf., Chapter 3), and HRSI knowledge is growing fast. However, most insights are still based on scenario-based experiments or Wizard of Oz experimental designs with service robots that are programmed in a decision-tree logic, rather than interactions with actual autonomous, self-learning service robots (cf., Chapter 3; De Keyser & Kunz, 2022). Hence, the results and derived conclusions of the present thesis are bound by the status quo of technological and HRSI knowledge at the time of their development.

7. Conclusion

The introduction of service robots has profound impact on service theory and practice (Wirtz et al., 2018). This thesis sheds light on customer interactions with digital and embodied service robots in external service encounters by synthesizing extant knowledge, deriving implications for successful service robot implementation, analyzing gaps in literature, and developing service encounter theory and new HRSI concepts (Chapter 2-4). Additionally, this thesis offers new insight in relation to employee interactions with digital service robots in internal service encounters by developing the concept of CI systems and empirically investing its effect on employee outcomes (Chapter 5). Due to exponentially increasing computer processing power, connectivity, ubiquitous computing and especially big data, AI-based technologies become more sophisticated by the minute and open up new and exciting interaction possibilities between service robots and customers and employees. It is hoped that this thesis contributes meaningfully to discussions on theory and management of (future) HRSI in service literature, that it moves the field forward, inspires future research, and that it provides actionable implications for service managers who introduce different service robot types into the service frontline.

Appendix

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Appendix A: Overview of Extant HRI Literature Reviews (Chapter 3)

Field	Source	Review objectives	Number. of articles analyzed	Multidisciplinary	Topic or outcome independent	Various social robot types suited for org. frontline	Service focus
Service Marketing/Management	De Keyser and Kunz (2022)	Establishing the **state-of-the-art of live and work with service robots** following a Theory-Context-Characteristics-Methodology; **Future Research Agenda**	88		☑	☑	☑
	Blut et al. (2021)	Analyzing if customers' **anthropomorphism of robots** (physical robots, chatbots, other AI) facilitates or constrains their use intention.	71	☑		☑	☑
	Xiao and Kumar (2021)	Development of **conceptual framework** including **antecedents and consequences of firms adopting and integrating robots into customer service operations**; Discussion of the degree of robotics adoption; Implications for managers.	n.s.		☑	☑	☑
	Lu et al. (2020)	Synthesis of **central research topics in business literature about the impact of service robots on customers and employees;** Future research agenda.	20		☑		☑
	Kaartemo and Helkkula (2018)	Identification of **themes on AI and robots in value co-creation in service**; Future research agenda.	49				☑
	Van Pinxteren et al. (2020)	Identification and classification of **service robot's (chatbots, avatars, robots) human-like communication behaviors**; Future research agenda.	61	☑			☑
	Ivanov et al. (2019)	**Overview of research on robotics in travel, tourism and hospitality**; Identification of research gaps and directions for future research.	131	☑	☑		
Robotics/Information Systems	Saunderson and Nejat, (2019)	**Review findings on robotic non-verbal communication**; Investigation of communication effects on humans: shifting, cognitive framing, eliciting emotional responses, triggering specific behavioral responses, and improving task performance; Future research agenda.	95			☑	
	Savela et al. (2018)	**Examination of the social acceptance of robot workers in different occupational fields**; Identification of positive and negative attitudes towards robots.	42	☑			
	Gasteiger et al. (2021)	**Synthesis** of existing literature on human factors to consider when designing robots that can be **personalized or localized** (transferred to other cultures).	42	☑		☑	
	Robaczewski et al. (2021)	**Overview** of every research **using the NAO** robot to see how the it can be used and **identify its potential** as a socially assistive robot.	51	☑	☑		
	Kachouie et al. (2014)	Review of **SAR in elderly care; Identification and classification of interventions, measures, and outcomes of field trials** of SAR in elderly care.	86	☑		☑	
	Robinson et al. (2014)	Identification **of areas of need of older people**, and respective **available robotic solutions; Critique of robotic solutions**; Future research agenda.	n.s.				

Field	Source	Review objectives	Number. of articles analyzed	Multidisciplinary	Topic or outcome independent	Various social robot types suited for org. frontline	Service focus
Healthcare/Psychology	Honig and Oron-Gilad (2018)	Understanding the way people **perceive, process, and act on failures in human robot interaction**; Model development of information processing for robotic failures in communication with humans.	52				
	Vandemeulebroucke et al. (2018)	Understanding how **older adults experience, perceive, think, and feel about the use of SAR** in aged care settings; **Identification of themes** related to the use of SAR in elderly care.	23	☑		☑	
	Oliveira et al. (2021)	**Scoping review** of quantitative studies that test HRI interventions; **Investigation** of prosocial behavior relationships	19	☑			
	Shishehgar et al. (2019)	**Categorization of problems encountered by older adults;** Identification of robot types deployed to overcome these problems**.**	58	☑		☑	
	Kabacińska et al. (2021)	**Overview and structure** of studies on robotic interventions in supporting childrens' mental health; future research agenda.	16			☑	
Education	Woo et al. (2021)	**Overview** of **field studies** with **social robots in classrooms**	23			☑	
	Tlili et al. (2020)	**Overview** of robot-assisted special education studies from the **perspective of Activity Theory**	20	☑			
	Galvez Trigo et al. (2019)	Identification of **the main reasons for low uptake of robots in Special Education,** obtained from an analysis of previous research and from interviewing Special Education teachers.	18			☑	
	Zhong and Xia (2020)	**Overview** of empirical evidence on the application of robotics in mathematics education; Future research agenda	20			☑	
	Review in Chapter 3	Reporting of **status quo of HRI research** across **scientific fields; Identification** of a **guiding structure** and of **implications for service researchers and practitioners** for a **successful integration of robots** in the frontline; **Identification of knowledge gaps.**	199	☑	☑	☑	☑

Note. n.s. = not stated; a similar version of this Table is published in the supplementary material of Blaurock et al. (2022).

Appendix B: Search Strings (Chapter 3)

Search	Boolean Phrase
May 2019	TS= ("healthcare robot*" OR "care robot*" OR "social robot*" OR "assistive robot*" OR "socially assistive robot*" OR "service robot*" OR "companion robot*" OR "education robot*" OR "social* intelligent robot*" OR "interactive robot*" OR "socially evocative robot*" OR "socially situated robot*" OR "sociable robot*" OR "rehabilitation robot*" OR "telemedicine robot*" OR "non-human service agent*" OR cobot* OR HRI OR humanoid* OR "collaborative robot*" OR "cooperative robot*" OR "anthropomorphic robot*" OR "human* robot*" OR "frontline service robot*" OR "assistant robot*" OR "commercial robot*")
	((TS=robot*) AND (WC=(Management OR Psychology OR Business)))
November 2021	((TS=robot*) AND (WC=(Management OR Psychology OR Business))) OR (TS= ("healthcare robot*" OR "care robot*" OR "social robot*" OR "assistive robot*" OR "socially assistive robot*" OR "service robot*" OR "companion robot*" OR "education robot*" OR "social* intelligent robot*" OR "interactive robot*" OR "socially evocative robot*" OR "socially situated robot*" OR "sociable robot*" OR "rehabilitation robot*" OR "telemedicine robot*" OR "non-human service agent*" OR cobot* OR HRI OR humanoid* OR "collaborative robot*" OR "cooperative robot*" OR "anthropomorphic robot*" OR "human* robot*" OR "frontline service robot*" OR "assistant robot*" OR "commercial robot*")) Timespan: 2019-2021

Note. The third search phrase combines the first and second Boolean phrases.

Appendix C: Inclusion and Exclusion Criteria (Chapter 3)

	Initial Screening (article titles and abstracts)		**Coding (full texts)**	
	Exclusion	*Inclusion*	*Exclusion*	*Inclusion*
Date	Any studies published before 1970	1970 – 2021 Nov	-	-
Language	Other languages	English	-	-
Sample	-	Any sample (children and 18+ years)	Children under the age of 5 and participants who have mental impairments (dementia, autism)	Healthy individuals from the age of 5+
Study Type	Book chapters, conference proceedings, editorials	Empirical and conceptual studies published in a peer-reviewed journals	Conceptual papers, scale development papers, studies that have no behavioral or psychological outcomes and no direct human-robot interaction	Quantitative and qualitative empirical studies on human robot interaction
Robot Type	Industrial / Mechanical robots, not-embodied robots like virtual assistants	Embodied, social robots that exhibit human-like behavior	Robots that cannot exhibit non-verbal communication (i.e., smart objects) or actively, socially interact with consumers	Same as initial screening
Scope	Addressing robot design, algorithm development for robots, robotic mechanics	Addressing some form of behavioral or psychological consequence for consumers of a direct or scenario-based interaction with an embodied, social robot	Same as initial screening	Same as initial screening
Journal Quality	Any article published in journals without WOS index	Articles published in WOS indexed journals	Articles published in journals without WOS index and in ESCI indexed journals, with an impact factor < 1.00 and ranked in Quartile 2,3 or 4 according to scimago.com	Articles published in SCI, SCI-E and SSCI indexed journals with impact factor > .99 and ranked in Quartile 1 according to scimago.com

Appendix D: PRISMA 2020 Checklist for Systematic Review Processes (Chapter 3)

Section and Topic	Item #	Checklist item	Location where item is reported and explanations related to the items
TITLE			
Title	1	Identify the report as a systematic review.	It is identified as systematic review in the title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Because we did not confirm and register PRISMA as the main protocol before starting the review process, we do not mention it in the Abstract.
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	We clearly describe the rationale of this review in the introduction section.
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	We clearly provide objectives and research questions in the introduction section.
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	All the inclusion and exclusion criteria were specified in the methods section and supplementary material (Appendix A). Clustering of studies based on the D^3 framework, service industry type, and study characteristics was specified in the methods section and Tables in the Appendix B.
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	We specified how and why we used the Web of Science database to collect our data. We also reported a timeline for searching and updating the data in a flowchart (Figure 5).
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	We presented which Web of Science categories, material types (Article), index (SCI-E, SSCI) and ranking score (www.scimago.com) were used.
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	We provide details about the screening procedure and how we used independent reviewers while screening titles, abstracts and full texts.
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	We reported data collection and coding, and double-checking processes in detail in the methods section.
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were	We reported all the coded information in the methods section. We clarified the usage of data extraction sheets.

Section and Topic	Item #	Checklist item	Location where item is reported and explanations related to the items
		sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	
	10b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	We reported all the coded information in the methods section. We described missing and unclear information in our coding file.
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	We reported using single database as risk of bias in the limitation section.
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results.	Not applicable because this review is not a meta-analysis.
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	We clarified how included studies were grouped based on the suggested definitions of design, delegate and deploy in the results section.
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Not applicable because this paper does not include quantitative synthesis.
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	We clearly reported the results of individual studies in the Appendix E. We also provided Table 3, Table 4 and Figure 7 which are related to descriptive statistics of all included papers.
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	We clarified how we followed an inductive approach while analyzing the final dataset. Statistical methods are not applicable because this paper does not include a meta-analysis.
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, meta-regression).	Not applicable because this paper does not include a meta-analysis
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Not applicable because this paper does not include meta-analysis
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Bias assessment is not applicable because this paper does not include quantitative data to test potential effects of biases, such as publication bias
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Certainty assessment is confidence to the estimated effect size. Therefore, not applicable because this paper does not include meta-analysis.
RESULTS			

Section and Topic	Item #	Checklist item	Location where item is reported and explanations related to the items
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Study selection process is described and visualized in Figure 5.
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	We cited a few of excluded papers (e.g., Banks, 2019) and explained why we excluded them.
Study characteristics	17	Cite each included study and present its characteristics.	We cited each included paper and presents details about them in the Appendix B
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Not applicable because this paper does not include meta-analysis
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g., confidence/credible interval), ideally using structured tables or plots.	We reported descriptive summary statistics for design, delegate and deploy in Table 4 and Figure 7. Others are not applicable because this paper does not include meta-analysis.
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	We summarize the characteristics of each study in the Appendix B. Risk of bias is not applicable because this paper does not include meta-analysis
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	We reported descriptive statistics for included papers. Other are not applicable because this paper does not include meta-analysis
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Not applicable because this paper does not include meta-analysis
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Not applicable because this paper does not include meta-analysis
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Bias assessment is not applicable because this paper does not include quantitative data to test potential effects of biases, such as publication bias
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Certainty assessment is confidence to the estimated effect size. Therefore, not applicable because this paper does not include meta-analysis that combines effect sizes.
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	We provided general interpretation in the discussion and conclusion sections.
	23b	Discuss any limitations of the evidence included in the review.	We reported using single database as a limitation in the discussion section.
	23c	Discuss any limitations of the review processes used.	We reported not using preregistration as a limitation in the discussion section.

Section and Topic	Item #	Checklist item	Location where item is reported and explanations related to the items
	23d	Discuss implications of the results for practice, policy, and future research.	We provide implications for practitioners in the discussion section.
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	While we executed data with the highest level of diligence and relied on independent coding procedures, we did not preregister the protocol for two main reasons. First, when we started our review process in 2019, PRISMA Protocol versions at the time as well as the suggested procedure by Siddaway *et al.* (2019) did not suggest pre-registration. Second, our review process includes exploratory and iterative elements (e.g., modifying some exclusion criteria after first search, recoding new variables during the analysis process), which are not suitable for pre-registration. We state that we did not preregister the review in our limitations section.
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Not applicable because the review process was not preregistered.
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable because the review process was not preregistered.
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	There was no financial support for this review. We thank our colleagues who friendly reviewed our paper.
Competing interests	26	Declare any competing interests of review authors.	There is no conflict of interest for this paper.
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	We provided the exact Boolean formula that we used in search process. We added this statement for the availability of the dataset and used extraction sheets: "The data that support the findings of this study are available from the corresponding author, Marah Blaurock, upon request."

References:

- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P. and Moher, D. (2021). The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews, *BMJ, 372* (n71), 1-9. http://dx.doi.org/10.1136/bmj.n71]. For more information, visit: http://www.prisma-statement.org/.
- Siddaway, A. P., Wood, A. M. & Hedges, L. V. (2019). How to Do a Systematic Review: A Best Practice Guide for Conducting and Reporting Narrative Reviews, Meta-Analyses, and Meta-Syntheses. *Annual Review of Psychology, 70*, 747–770.

Appendix E: Overview of Key Insights from HRSI Studies along the D^3 Framework (Chapter 3)

Here we provide a detailed list of all articles included in the analysis is provided. The articles are organized first based on the related D^3 framework theme (i.e., design, delegate, deploy) and second, according to the study contexts to provide a reader friendly directory of extant literature on consumer interactions with social robots. The six articles (i.e., Chita-Tegmark et al., 2019; Dou et al., 2022; Jung et al., 2021; Leo & Huh, 2020; Li et al., 2010; Mende et al., 2019) that conduct cross-context studies are listed in each of the respective service contexts.

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Table E1. Summary of key insights from HRSI studies under the **design theme**

Table E1.1. Summary of key insights from design theme: Behavior (software)

Hospitality & Tourism *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Socially Interactive Services	**Hotel** Robot concierge use figurative vs. literal language style	NAO, humanoid	**Cognitive** Service encounter evaluation	Results of the online experiment (n=173) with humanoid robot *NAO* show that literal (vs. figurative) language used by a service provider might be more congruent with conversational norms, thus leading to better customer evaluation in robots (due to anthropomorphism), humans but not in kiosks. Perceived credibility fully mediates the effect between language style and service evaluation.	Choi et al., 2019a
	Hotel 1 robot vs. 2 robots in conversation- indirect vs. direct speech: greeting & providing information, to hotel guests		**Behavioral** Showing interest in robot	Two field experiments (n=50 each) with humanoid *NAO* robots found no significant difference between using dual robots' and a single robot's indirect speech. Robot's speech is the main factor that affects people's behavioral interest response.	Pan et al., 2015
Assistive Services	**Restaurant/Bar** Perceived human-likeness & intelligence of robot when serving in restaurant	X1; X2, humanoid, machine-like	**Cognitive** Rapport, Invitation, Comfort, Care	Perceived human-likeness and intelligence positively affects customer-robot rapport building and the hospitality experience as was found in a scenario-based experiment with humanoid and machine-like robots (*X1; X2*) (n=148).	Qiu et al., 2020
	Restaurant/Bar Mechanical vs. humanoid robot bartending	Pepper, humanoid; Mechanical robot	**Behavioral** Adoption intention **Cognitive** Expectations, Trust	The results of a scenario-based experiment (n=533) show that consumers with higher propensity to trust technologies in general expect intelligent robots, including robot bartenders, to be functional, helpful, and reliable. However, a negative attitude toward robots in general is still a significant barrier to developing trust in intelligent robots among consumers. If trust is established, it drives adoption intentions. The physical form of robots does not affect trust in this study.	Tussyadiah et al., 2020

	Hotel Serving customers with robots in China hotels, usefulness, sentimental value of robots and consumers' self-efficacy	NA	**Behavioral** Behavioral intention	The results of the survey study (n=217) confirm the technology acceptance model and attitudes. The study perceived that the value has a positive impact on behavioral intentions. Usefulness, ease of use and sentimental value had an indirect effect on behavioral intentions.	Zhong et al., 2021
Assistive and Socially Interactive Services	**Restaurant/Bar** Different humanoid robots greeting, taking orders, delivering foods	Various humanoid robots	**Behavioral** Customer decision, (Intent to use, Intent to recommend)	In a photo-based survey (n=517), results show that attributions mediate the relationships between affinity toward the robot and customer behavioral intentions to use and recommend service robots. Specifically, customer's affinity toward the robot positively affects service improvement attribution, which in turn has a positive influence on customer behavioral intentions. Further, affinity negatively affects cost reduction attribution, which in turn has a negative effect on behavioral intentions. Human-likeness has a positive influence on affinity.	Belanche et al., 2020
	Hotel Different morphologies of robot concierge in hotel	Humanoid, zoomorphic/ caricatured, android, machine-like robots	**Behavioral** Adoption intention **Cognitive** Preference for human vs. robotic service	In a scenario-based experiment (n=186), results demonstrate that the robot's morphology significantly influenced guests' attitudes toward robot concierges. The caricatured robot was the most preferred morphology of robot concierges. Nevertheless, the study also shows that even if guests had favorable attitudes toward robot concierges, they preferred human employees to robot concierges because of humans' sincere and genuine interactions.	Shin & Jeong, 2020
	Travel agent Planning a trip	NAO, humanoid	**Behavioral** Proximity to robot **Cognitive** Technology acceptance, Negative attitudes towards robots, Trust in autonomous systems, Trust in autonomous systems, Robot acceptance, Predictability, Reliability, Competence, Anthropomorphism, Uncanniness	In this lab experiment (n=31) in which participants interacted with a robot in different settings (small talk vs. trip planning service) researchers found that directed gaze during the small talk was perceived as more humanlike and was more accepted than a random gaze. Second, an interaction effect of dialog content order and initiative was found but not as expected. When having the service task as the first interaction, participants trusted the robot more when the robot had the initiative compared to the human initiative. This effect was reversed when the service task was the second interaction. Finally, the participant's self-reported trust in the robot was associated with a smaller distance they kept to the robot.	Babel et al., 2021

	Hotel Functional and emotional aspects of robots	Various robots, humanoid, machinelike	**Behavioral** Intention to use robot assistants, Clusters of consumers	The results of this survey study (n=494) revealed four types of hotel consumer groups via cluster analysis: The Ordinary, Enthusiastic adopter, Tech laggard, and Value seeker. These four clusters are differed based on the functional and emotional aspects of consumers' robot experiences.	Lee et al., 2021
	Restaurant Perceived value of the robot (functional, emotional, social, epistemic, co-creation, conditional), Covid-19 related needs (need for physical distancing, mysophobia)	Humanoid, machinelike	**Behavioral** Willingness to use, Willingness to pay more	Results of this survey study (n=445) perceived value of the robot dimensions predict willingness to use and willingness to pay more. Covid-19 related antecedents improve conditional value of robots.	Chuah et al., 2022

Education *Antecedents / Service Settings*		*Robot Type*	*Outcomes*	*Key findings*	*Authors*
Educational Approach	Educational Robot-Based Learning System vs. PowerPoint-based learning system	Robotis, humanoid	**Cognitive** Learning, Self-efficacy, Motivation **Behavioral** Concentration, Engagement	The experiment with children (n=52) demonstrates that the robot-based learning system improved student performance more than the PowerPoint-based learning system did. The experimental results indicate that the students were motivated to use the educational robot-based learning system (i.e., Robotis).	Chin et al., 2014
	Expressive vs. flat active reading	Tega, zoomorphic / comic-like		The results of the experiment with children (n=45) indicate that there was no difference in children learning between the expressive and flat Tega robot reading conditions. However, as compared to children in the flat condition, children in the expressive condition were more concentrated and engaged as showed by their facial expressions and their retelling of the robot story. Taken together, these results suggest that children may benefit more from the expressive robot than from the flat robot.	Kory Westlund et al., 2017
	Robot learning modes: learning vs. no learning & continuous learning vs. non-learning vs. personalized learning	NAO, humanoid		In two field experiments with the goal of teaching children (n=25; n=37) handwriting in a learning-in-teaching approach with social robot NAO, children learnt best in the robot learning mode (i.e., the robot exhibits learning competency). However, the robot's competencies did not affect children's self-efficacy towards tutoring the robot. Children were highly	Chandra et al., 2020

			motivated to interact with the robot. Further, children's learning and perceptions of the robot changed as interactions unfold, confirming the need for longitudinal studies.	
Robot instructions style: storytelling, oral reading, cheerleader, action command, and question-and-answer mode.	Robosapien, humanoid	**Cognitive** Robot roles	The results of the field in one school classroom study suggest that humanoid robots like Robosapien could be used as communication mediators to support classroom learning. Five scenarios in this study also highlighted the effectiveness of supporting a teacher with a robot in an elementary language course. Students were highly motivated to learn.	Chang et al., 2010
Three robot roles as a pedagogical agent: Tutor vs. tutee vs. Peer	Tega, zoomorphic / comic-like	**Affective** Emotional engagement **Cognitive** Learning	The experiment with children (n=59) show that the peer-like pedagogical robot (i.e., robot Tega programmed to exhibit both behaviors of tutor and tutee) promoted children's greatest vocabulary learning and affective engagement among the three robot conditions.	Chen et al., 2020
Robot interaction behavior in robot-assisted language learning: interviewer vs. narrator vs. facilitator vs. interlocutor	Furhat, humanoid	**Cognitive** Preference interaction collaboration Learning	The experiment with adult second language learners (n=33) suggests that learners preferred the robot (i.e., anthropomorphized robot head Furhat) behavior that focused on interviewing one learner at the time, but that they were the most active in sessions when the robot encouraged learner–- learner interaction.	Engwall & Lopes, 2022
Robot language teaching styles (i.e., Interviewer, Narrator; Facilitator, Interlocutor)	Furhat, humanoid	**Cognitive** Learners' Satisfaction	In a lab experiment with humanoid robot Furhat teaching adult participants Swedish (n=32) using four different teaching styles, results indicate that the Interviewer style was preferred most. However, the ratings were highly dependent on individual factors indicating that the individual preferences need to be anticipated in order to improve learner satisfaction with robot teachers.	Engwall et al., 2021
Person-centered vs. Task-centered behavior during teaching	No description of robot's capability or appearance	**Cognitive** Acceptance, Trust, Robot's emotional intelligence (EI)	In a video-based experiment (n=188), it was found that for scenarios describing a robot that acts in a person-centered manner, the robot will not only be perceived as having higher EI (p=.003) but will also cause people to form more positive impressions of the learner that the robot teaches (p<.001).	Chita-Tegmark et al., 2019 *(article also in healthcare context)*
Social (i.e., greeting, encouraging, personalized speech, supporting gestures, enthusiasm) vs. neutral behavior	NAO, humanoid	**Cognitive** Learning	The results of the experiment with children (n=86) show that on average, students significantly improved their performance even after 3 occasions of 5-min exercises. Beyond-average pupils profited most from a robot tutor, whereas those below average in multiplication benefited more from a robot that showed neutral rather than more social behavior.	Konijn & Hoorn, 2020
Bilingual robot vs. monolingual robot			Findings of the experiment with children (n=67) demonstrate that using a robot tutor to teach children second language words contributed to both vocabulary learning and target word retention. The majority of children preferred interacting with the bilingual robot, but children's preference did not affect word learning.	Leeuwestein et al., 2021

	Robot's interaction style: friendly vs. authoritarian vs. neutral	Pepper, humanoid	**Behavioral** Compliance level **Cognitive** Cognitive performance	Results of the lab experiment with students (n=60) show that the authoritarian interaction style seems to be more appropriate to improve the performance when the tasks require high cognitive demands.	Maggi et al., 2021
	Robots exhibiting social behaviors	Various humanoid social robots	**Cognitive** Robot acceptance, Intention to use	Survey of university students (pre-service teachers; n=121) shows that there is a critical disjunction between researchers' efforts to equip social robots with human manners and social intelligence and participants' rejection of this technology precisely because it mimics being human.	Istenic et al., 2021
	Robot using different voice types and head color codes	Alpha, humanoid	**Cognitive** Warmth, Competence, Discomfort	In this scenario-based experiment (n=34) in three different service contexts (i.e., domestic services, retail, and education), the optimal voice (male vs. female vs. child) and head-light colors (warm vs. neutral vs. cold) for robot design was explored. Results revealed that male voices are suitable for education field as they are associated with higher competence compared to the other voices. With regards to head-light colors, neutral colors are the optimal choice for all three application fields. Still, even though cold colors cause more feelings of discomfort, they can be used as a second choice to express high competence and efficiency in education settings to meet the requirements of special situations.	Dou et al., 2022 *(article also in retail and domestic services)*
Robot Non-verbal Behavior	Refrained vs. normal Evaluative vs. non evaluative gaze	Robovie-R2, humanoid	**Behavioral** Participation **Cognitive** Preference, Trust	The experiments with students (n=188) show that when a humanoid robot Robovie-R2 advises learners in foreign-language education, people with a lower Fear of Negative Evaluation (FNE) prefer normal to refrained gaze - which reduces their intention to participate. Moreover, the experimental results suggest that persons having higher FNE tend to trust the robot more, and participants spoke more when the robot did not evaluate them and when it used the normal gaze.	Nomura & Kanda, 2015
	Deictic condition (robot uses pointing gesture) vs. speech-only condition	Humanoid robot	**Behavioral** Frequency of asking questions	The results of the experiments with children (n=92) show that they were inclined to ask significantly more questions in the condition in which a humanoid robot had deictic interaction capabilities.	Komatsubara et al., 2018
	Personalized non-verbal behavior (gaze, movement), verbal behavior (friendliness), and adaptivity of progression (to personal performance)	NAO, humanoid	**Cognitive** Learning	The results of the experiment with children (n=59) and NAO robot show that children's learning (i.e., application of knowledge to a new context) of a novel subject was higher in a personalized robot experimental condition compared to a non-personalized robot condition.	Baxter et al., 2017
	Robot-assisted tutoring with or without iconic gestures (gestures that visualize target words)		**Cognitive** Anthropomorphism, Vocabulary learning	Results of the field experiment with children (n=104) show that children tended to anthropomorphize the robot prior to and after the tutoring session to a similar degree. Children did not anthropomorphize the robot more when it used iconic gestures.	van den Berghe et al., 2021

Elderly Care		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Antecedents / Service Setting					
Assisted living services: • **Shopping services** • **Garbage disposal** • **Physical walking support indoors and outdoors** • **Delivering objects (e.g., food and drinks)** • **Navigation, opening and closing doors** • **Domestic services (e.g., folding towels, laundry)**	Re-enablement coach robot - motivates and stimulates whenever someone is still capable of performing a task themselves	Care-O-bot 3, machine-like	**Cognitive** Tensions between autonomy and independence	Through scenario-based focus groups, participants (n=122; older adults, formal and informal caregivers) acknowledged that a re-enablement coach robot (i.e., robot providing functionality lost through frailty or disability) would create tension between respecting the autonomy of the user (i.e., robot obeys all commands given by the user) and the promotion of independence in the long term (i.e., robot is programmed to maintain the abilities the user still has).	Bedaf et al., 2016
	Robot role (Assistant vs. Companion robot), Demeanor (Playful vs. Serious Demeanor)	HomeMate, machine-like	**Affective** Robot anxiety **Cognitive** Social attractiveness, Robot eeriness, Perceived intelligence	The results of the experiment with older adults (n=59) show that assistant robots are perceived as more socially attractive and intelligent when their demeanor is playful rather than serious. In addition, companion robots are evaluated as less anxious and less eerie when their personality is serious rather than playful.	Sundar et al., 2017
	Food delivery with speech vs. tablet control	Robot-Era - SCITOS G5 by MetraLabs, humanoid	**Cognitive** User preference of HRI interface	This paper evidences a field experiment in which older adults (n=15) controlled a robot performing a food delivery task either via speech or touch screen tablet. The findings suggest no significant difference between the two types of user interfaces.	Wang et al., 2019
Socially assistive services: • **Agenda-keeping** • **Medication reminder** • **An interface with smart home solutions** • **Making (video) calls** • **Advising (e.g., nutrition intake)** • **Motivating for physical activity** • **Safety monitoring and alerting in case of an emergency** • **Social companionship**	Robot service enablement and Robot mediation	PaPeRo, humanoid	**Cognitive** Service innovation, Social vulnerability	The results of the survey with healthcare professionals (n=335) indicate that (1) robot service enablement (Aged Care Service Reliability, Service Cost, and Service Safety) and robot mediation (Personalized service, Delivery, Entertainment, Social connectivity) can positively improve aged care service innovation; (2) aged care service innovation can reduce social vulnerability by improving socioeconomic accessibility of and community ties among older people.	Khaksar et al., 2016
	Medication reminders and advices, social connectedness, fall detection and alerts	Care-O-bot 3, machine-like	**Affective/ Cognitive** Values	Twenty-one (21) scenario-based focus groups with older adults, formal and informal caregivers (n=123) suggest that user autonomy assumes primacy over other values. The topic of safety was found to be more important than anticipated. The participants favored compromise, persuasion and negotiation as a means of reaching agreement.	Draper & Sorell, 2017
	Engage in conversation, listen to music, watch videos, play games, and to contact loved ones via text, video messages, video or audio call	Pepper, humanoid	**Cognitive** Health-related quality of life, Mental health, Loneliness	This intercultural study was conducted in England and Japan (n=33). Participants interacted with a more vs. less culturally competent socially assistive robot. While there were no significant differences related to participant's health between the treatment and control group, mental health (emotional well-being) and loneliness scores were slightly higher in the group with the culturally competent robot.	Papadopoulos et al., 2022

Socially interactive services: • **Personal communication (e.g., greeting, asking and answering questions, gestures)** • **Entertaining and joking** • **Engaging in a joint game (e.g., Bingo)** • **Participatory arts (e.g., theatre)** • **Playing music** • **Information providing (e.g., giving weather forecast and television program overview, reviewing news)**	Verbal communication, answering and asking questions	Peoplebot, machine-like	**Cognitive** Attitudes towards the robot	The results of the experiment with older adults (n=20) uncover a trend for men to evaluate the robot more highly than women. Participants' positive attitudes towards robots before the robot interactions were associated with positive robot evaluations after the interactions.	Stafford et al., 2014a
	Engaging in a joint game, verbal and non-verbal communication, showing emotions: neutral, happy, angry, sad; showing confidence; showing surprise	NAO, humanoid	**Affective/ Cognitive** Values	The results of the experiment with elderly people (n=19) suggest that a robot playing games with people has entertainment value. Robot's behavioral patterns (i.e., combination of gestures, eye LED patterns, and verbal expressions) encouraged older adults' interaction.	Johnson et al., 2016
	Engagement activities - providing assistance in art performing		**Affective** Psychological wellbeing	The result of the experiment with older adults (n=15) show that after engaging with a socially interactive robot in a Shakespeare participatory art activity participants reported improvements in mood, loneliness, and depression.	Fields et al., 2019

Healthcare *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Verbal Medical Assistance Delivering medical class on diabetes; Greeting the user, reminding users of medicine intake, guiding the user to use the touch interface for medical advice; Providing information about patient's condition;	Introverted vs. extroverted robot	Pepper, humanoid	**Cognitive** Preferences for robot as educator for diabetes	In a field experiment (n=46) researchers found that that the majority of people who came to the experiment were extroverts (80.4%) and prefer to interact with extrovert robots (69.6%), therefore supporting the similarity-attraction effect (67.4%). However, the scholars could not find any relationship between the participants' personality score in the Big Five questionnaire and his/her preference about the robot.	Esteban et al., 2022
	Robotic vs. empathetic/emotional voice	Healthbot, humanoid	**Cognitive** Perception of empathy, Preference for voice type, Reasons for voice preference	In video-based experiments (n=120), researchers found that the most influencing factors for preferring the empathetic voice was the tone and emotions in the voice, closely followed by friendliness in the voice. People could also perceive empathy, concern and encouragement in the voice, which also contributed to their choice. The participants preferred the empathetic voice over the robotic voice for a healthcare application. The researchers also found that participants can perceive empathy from the healthcare robot's voice when empathy was expressed only by the prosody component of speech.	James et al., 2020

Medical receptionist (checking in for a doctor's appointment, collecting prescriptions); Medical Recording and Consultancy	Robot Communication (Changes in voice pitch, self-disclosure, Forward lean)	NAO, humanoid	**Behavioral** Engagement, Attention, Eye gaze, Forward lean smiling, Laughing **Cognitive** Perceived robot empathy	In a lab experiment with humanoid robot NAO in the role of a medical receptionist, participants (n=181) were more engaged, paid more attention to the robot, and leaned forward when it uses self-disclosure and forward-lean moves. In the self- disclosure condition participants laughed more. No effect of voice-pitch was found. There was no difference in perceived robot empathy between the conditions.	Johanson et al., 2019
	Polite vs. Impolite Demeanor		**Behavioral** Intention to comply	Results of a lab experiment (n=118) with humanoid robot *NAO* show that perceived politeness negatively affects the perceived benefit of compliance and intention to comply in a healthcare context. Direct speech with polite gestures increases patient compliance with healthcare advice provided by robots.	Lee et al., 2017
	Patient-centered vs. Task-centered	Not specified	**Cognitive** Acceptance, Trust, Robot's emotional intelligence, acceptance, Genera impression	This vignette-based study (n=188) shows that a robot displaying patient-centered robot behavior is perceived as more emotionally intelligent and impressive by patients than task-centered robots. 4Results replicated in other domains such as dieting (n=91), learning (n=91), and job training (n=67).	Chita-Tegmark et al., 2019 *(article also in education context)*
Physical Medical Care Cleaning arm	Robot Touch (Aim of touch: Instrumental vs. Affective) Robot Warning Before Touch	Cody, machine-like	**Cognitive** Perceived intent, Positive and negative attitude towards robot	Perceived intent of the machine-like robot *Cody* when attempting to clean an arm in a medical context significantly influenced people's (n=56) response towards a robot's touch in a lab experiment. Verbal warning prior to the robot's touch was perceived as less favorable than no-warning.	Chen et al., 2014
Physical + Verbal Medical Care Measuring blood pressure, talking to patients	Robot language style in medical care	Telepresence robot, machine-like	**Affective** Impression of robotic voice, Emotions **Cognitive** Positive and negative attitude towards robots	Robot's language accent (New Zealand vs. the US vs. the UK) has an effect on participants' (n=92) emotions and attitudes towards robots (Telepresence robot) when measuring blood pressure. New Zealand accent is perceived as less robotic and leads to more positive attitudes towards robots.	Tamagawa et al., 2011

Domestic Services *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assisted living services	Household assistant, packing boxes, unpacking boxes, engaging in conversation, pointing out objects, giving instructions	Honda, humanoid	**Cognitive** Human-likeness, Likability, Shared reality future contact intention	The results of the lab experiment with adults (n=62) suggest that when the robot used co-verbal gestures during HRI (i.e., when it was anthropomorphized more), participants perceived it as more likeable, reported greater shared reality with it, and showed increased future contact intentions than when the robot gave instructions without gestures. These findings show that communicative non-verbal behaviors (i.e., hand and arm gestures) displayed by robotic systems affect anthropomorphic perceptions and the mental models that humans form of a humanoid robot during the interaction.	Salem et al., 2013
	Fetching and carrying household items and drinks, setting the table, and opening drawers and doors	Care-O-bot, mobile robot assistant	**Behavioral** Accepted distance	The results of the lab experiment with adults (n=30) show that the robot's behavior (speed and speed profile) significantly affect distances that humans are willing to accept between themselves and an approaching robot. The experiment also confirms the existence of a habituation effect. As participants got more acquainted with the robot, they were willing to accept smaller distances between them.	Brandl et al., 2016
	Personal household assistant, reminding of tasks, fetching things	MyBom2, cartoon-like	**Cognitive** Perception of privacy concern	The results of two lab experiments (n=36; n=20) revealed that robot behaviors that help make a privacy-protection measure noticeable are effective in reducing privacy concerns of users. Moreover, the combination of three behaviors (i.e., gaze, distance, clarity) was effective in reducing more privacy concerns; while a single effective behavior (e.g., turning around) could suffice if computational resources for behavior execution are scarce. Lastly, people tended to be more sensitive in situations if body exposure or nakedness is involved.	Yang et al., 2022
	Turning on lights, selecting music, carry out prompts, e.g., drive to a specific location, or reproduce information, answer questions and [list activities on demand/ autonomously propose and plan activities	Viva, humanoid	**Affective** Trust, No. of positive entries **Cognitive** Trust, Likeability, Femininity, Masculinity	The results of a scenario-based study which included an additional collection of qualitative data (n=163) showed that autonomy did not impact objective ambivalence. However, subjective ambivalence was higher towards the robot high versus low in autonomy. Furthermore, this effect turned non-significant when controlling for individual differences in technology commitment. Qualitative results were categorized into assets (e.g., assistance, companionship) and risks (e.g., privacy/data security, social isolation).	Stapels & Eyssel, 2022
Assisted living & socially assistive services	• (1) physical task: fetch and carry • (2) cognitive task: cognitive prosthetic	Sunflower, humanoid AIBO, zoomorphic	**Cognitive** Perceived task load - NASA Task Load Index	The controlled experiments were integrated with open-ended scenarios as part of a longitudinal study with eight participants (n=8). In the physical task, there was evidence of adaptation to the robot's behavior. For the cognitive task, the use of the robot was experienced as more frustrating in the later weeks.	Syrdal et al., 2015

Socially assistive services	Helps users find a TV program that fits their interests	iCat - zoomorphic with humanoid features	**Cognitive** Robot personality (Big 5), Perceived usefulness, Enjoyment, Ease-of-use, Control & recommendation appreciation	The results of the experiment with adults (n=17;32) show that when the robot exerted an extroverted personality (through facial expressions, motion, linguistic style, and speech), participants perceived it as more agreeable, less conscientious, and more open to new experiences. The results of the lab experiment suggest that the most preferred combination is an extrovert and friendly personality with low user control. Furthermore, it was found that the robot's personality affects the perceived level of control.	Meerbeek et al., 2008
	• Domestic Security – alerting when detecting a suspicious intrusion outside the room • Domestic Healthcare - measuring the body temperature and blood pressure of the participant	Humanoid robot with human facial features	**Affective** Affective evaluations **Cognitive** Cognitive evaluations and acceptance	The experiments with students (n=164) confirmed that matching gender-occupational role (i.e., security=male role, healthcare=female role) and personality-occupational role stereotypes result in positive user responses, measured through cognitive and affective evaluations, subjective norms, perceived behavioral control, trust, and acceptance.	Tay et al., 2014
Socially interactive services	Moving around, entertaining, domestic help, engaging in conversation, dancing, laughing, touching, and shaking hands	Zoomorphic socially interactive robot	**Affective** Perceived enjoyment **Cognitive** Usefulness, Attitude	The results of the experiment with 210 participants show that the social presence is key to the behavioral intention to accept social robots. The proposed model shows the significant roles of perceived adaptivity and sociability, both of which affect attitude as well as influence perceived usefulness and perceived enjoyment, respectively. These factors can be key features of users' expectations of social robots, which can give practical implications for designing and developing meaningful social interaction between robots and humans.	Shin & Choo, 2011
	Not fully specified, domestic companion robot using different voice types and head color codes	Alpha, humanoid	**Cognitive** Warmth, Competence, Discomfort	In this scenario-based experiment (n=34) in three different service contexts (i.e., domestic services, retail, and education), the optimal voice (male vs. female vs. child) and head-light colors (warm vs. neutral vs. cold) for robot design was explored. Results revealed that children's voices are more suitable for the field of home companion because of their high warmth. Moreover, female users have a particular dislike for male voices in home companion robots; therefore, male voices should be avoided in such applications. With regards to head-light colors, neutral colors are the optimal choice for all three application fields. Still, warm colors can be the second choice in home companion robots because of their high warmth and low discomfort ratings.	Dou et al., 2022 *(article also in education and retail context)*

Public Services *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Public Services (University campus)	Assisting/ Guiding (university campus) Robotic gaze turn-taking cues (no cues condition: human-like appearance vs. cues condition: human-like social functioning)	Pepper, humanoid	**Affective** Emotional experience (Enjoyment, Interaction comfort) **Behavioral** Intent to use **Cognitive** Attitude, Anthropomorphism, Trust	Results of a field experiment with humanoid robot *Pepper* (n=114) in the Netherlands show that when perceived interaction comfort is high, perceived anthropomorphism is significantly higher for a robot without gaze turn-taking cues. Hence, the increased human-like appearance outweighs social functioning in terms of encouraging anthropomorphism toward service robots. Further, perceived anthropomorphism drives trust in *Pepper* and trust has a positive effect on perceived enjoyment which in turn enhances intentions to use service robots.	van Pinxteren et al., 2019b
	Guiding task at university campus Robot's service failure recovery (Knows how error occurred and apologizes or not)	ROBO-GUIDE, machine-like	**Behavioral** Intention to use **Cognitive** Capability, Likeability, Trust	Results of a video-based experiment (n=362) showed that brief, targeted interactions from a robot can significantly impact individuals' attitudes and intentions towards it. The research found that a robot offering an apology for an error supports individuals' perceptions of its likability and in turn individuals' intentions to use the robot. In contrast, a robot communicating its competence and apologizing do not impact users' intentions to use the robot.	Cameron et al., 2021
	Robotic student counselor	NAO, humanoid (Touch vs. no touch)	**Behavioral** Time of interaction, Compliance with robot request, Laughing, Smiling, Prosocial behavior **Cognitive** Negative attitudes towards robots, Perceived closeness, Warmth general evaluation of the counseling interaction	In a lab experiment (n=48), results reveal that participants mostly reacted by smiling and laughing when interacting with the robot. Students who were touched by the robot complied significantly more frequently with a request posed by the robot during conversation, and reported better feelings compared to those who were not touched; there were no effects of robot touch on subjective evaluations of the robot or on the interaction experience.	Hoffmann & Krämer, 2021
Various security robot contexts	Peacekeeping in streets Politeness of robot	Knightscope, humanoid	**Cognitive** Fairness, Friendliness, Appropriateness, Intimidating, Politeness	Results of three scenario-based experiments (n=99;118;101) with peacekeeping robot *KNIGHTSCOPE* show that polite robots are perceived as friendlier, fairer, and as acting in a more appropriate way and were also perceived as less intimidating.	Inbar & Meyer, 2019

	Access control to restricted areas of reliable vs. non reliable robot stating different social intentions (benevolence toward the visitor vs. toward the building occupants vs. toward the robot, and vs. toward the visitor with self-sacrifice)	Baxter Autonomous Security Robot (ASR), humanoid	**Cognitive** Trust, Trustworthiness (Benevolence, Integrity), Preferred use context	Results of a video-based online experiment (n=320) indicate that humans are more trusting of a reliable (i.e., correct rejections versus false alarms) security robots Further, stated social intent that is described as self-preserving is considered less benevolent and possessing lower integrity relative to all other forms of stated social intent (benevolence) than self-sacrificial robots. Results indicate a fairly low desire to use the ASR across all contexts, however humans prefer ASRs in military domains more than public domains.	Lyons et al., 2021

Retail *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Retail	Robot provides personalized (based on age, gender and game progress) services in the context of VR games to consumers in game shops in informal vs. respectful voices and with a female vs. male voices	Not specified, humanoid	**Cognitive** Satisfaction	The results of this field experiment (n=287), revealed that it is beneficial that the robotic attendant utilizes customer-specific attributes to provide personalized services; for female customers, it is recommended that a male robot voice is used.	Park et al., 2020
	Robot using different voice types and head color codes at a shopping reception.	Alpha, humanoid	**Cognitive** Warmth, Competence, Discomfort	In this scenario-based experiment (n=34) in three different service contexts (i.e., domestic services, retail, and education), the optimal voice (male vs. female vs. child) and head-light colors (warm vs. neutral vs. cold) for robot design was explored. Results revealed that male voices are suitable for the shopping reception setting as they are associated with higher competence compared to the other voices. With regards to head-light colors, neutral colors are the optimal choice for all three application fields. Still, even though cold colors cause more feelings of discomfort, they can be used as a second choice to express high competence and efficiency in the shopping reception setting to meet the requirements of special situations.	Dou et al., 2022 (*article also in education and domestic context)*

Arts & Entertainment *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Socially Interactive/ Entertaining Services	**Bar** Comedy Performance with changing gaze behaviors Telling jokes, playing music	RoboThespian, humanoid	**Affective** Emotional experience, (Happiness)	Audience participants (n=50) of comedy lab show more positive response towards the robot, when the robot directly "looks at them, negatively when it looks away".	Katevas et al., 2015
		Legomindstorm in 3 different forms (i.e., machine-like, humanoid, zoomorphic)	**Cognitive** Preference: Robot likability, Trust, Satisfaction	In a lab experiment (n=108) with students from three different cultures (Germany, Korea, China), an effect of interaction performance (active response and engagement) and preference (likeability, trust and satisfaction) in the human-robot interaction was found. A robots' anthropomorphic appearance increased likeability in all contexts. Compared with German participants, Chinese and Korean participants perceived the sociable robots to be more likeable, trustworthy and satisfactory, and they had higher engagement with the robot.	Li et al., 2010 *(article also in retail and education context)*
Assistive & Socially Interactive Services	**Sightseeing** Speech rate when providing information on sights	Robovie – II, humanoid	**Cognitive** Comprehension, Competence, Credibility	Two lab experiments (n=28; n=48) reveal that a humanoid robot (Robovie-II) using normal or moderately slow speech when providing information to customers is perceived as competent. In a situation where the robot and participants talk while walking, slow speech was the most comprehensible.	Shimada & Kanda, 2012
	Sightseeing Guidance role in Kyoto, explaining sights; Different humanoid robots (biped vs. wheeled, mechanic eyes vs. face display) vs. human	ASIMO, Robovie, humanoid	**Behavioral** Verbal response to robot **Cognitive** Impression (Familiarity, Novelty, Safety, Interaction)	In a lab experiment, verbal behaviors of participants (n=48) were not changed by robots' (ASIMO and Robovie) appearances but non-verbal behaviors (distance and response time) were affected. ASIMO received better impressions from participants than Robovie. Participants respond to humans faster than robots and more rapidly respond to ASİMO than Robovie. Those results are explained by impressions and attributions of different robot types.	Kanda et al., 2008

Table E1.2. Summary of key Insights from design theme: Appearance (hardware)

Hospitality & Tourism *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assistive and Interactive Services	**Hotel** Robot Appearance	Humanlike (male and female), machinelike, mascot-like	**Affective** Positive emotions **Behavioral** Willingness to accept use of service robots **Cognitive** Performance and effort expectancy	According to the results of the scenario-based experimental studies (total n=251) human likeness cause higher performance expectancy, mascot-likeness cause more positive emotions and machine-like appearance increase effort expectancy more than others. In humanlike and mascot-like conditions, increases in consumer acceptance are moderated by the sense of humor of service robots.	Zhang et al., 2021
No explanation about the functions of robots	**Hotel** Robot anthropomorphism	Humanlike (low vs. medium vs. high)	**Behavioral** Booking intention **Cognitive** Covid-19 prevention efficacy Attitudes	According to the results of this experimental study (n=711), robots are perceived as a reducer of Covid-19 contagion. Anthropomorphism is also positively related with COVID-19 prevention efficacy, positive attitudes, and higher booking intentions.	Romero & Lado, 2021
Low expertise (receiving guests at a hotel front desk	**Hotel** Five types of humanoid robots less or more resembling humans	Five types of humanoid robots less or more resembling humans	**Affective** Favorability **Cognitive** Trust	The results of the scenario-based experiment with an online panel of adults (n=505) show that affective and cognitive responses were more positive for the high-expertise humanoid (tutoring) than for the low-expertise humanoid (hotel reception) in all stages of the Uncanny Valley Theory except for the last stage, where the humanoid's face is the same as a human's face.	Jung et al., 2021 *(article also in education contexts)*
Assistive and Interactive Services	**Restaurant** Robot anthropomorphism Social Presence (Study 1) Utilitarian and hedonic value (Study 2)	Amy, humanlike Akatar, machine-like	**Behavioral** Customer repatronage/loyalty **Cognitive** Anthropomorphism, Social presence, Value perceptions, Augmentation opportunities	Results of a survey of restaurant customers who interacted with a robot (n=108) demonstrated that anthropomorphism is positively related with social presence, utilitarian, and hedonic value. The subsequent scenario-based experiment (n=361) revealed that both utilitarian and hedonic value of the robot positively affect repatronage intentions.	Odekerken-Schröder et al., 2022

Education *Antecedents / Service Settings*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Robot morphology	**Embodiment:** Social robots vs. virtual agents vs. humans	NAO, humanoid	**Cognitive** Learning, Attitudes, Perception of social presence	The results of the experiment with students (n=40) indicate that the participants who saw the video of the virtual human lecturer recalled less information than those who saw the recording of the human lecturer. However, when the actual lecturer was replaced with the NAO humanoid robot, knowledge recall was higher with an animated robot than a recording of a real robot. This effect on knowledge recall was moderated by gender. Attitudes were more positive toward human lecturers than toward robots.	Li et al., 2016
				The results of the experiment demonstrate that children (n=28) overcome strong incorrect biases in the material to be learned, but with no significant differences between embodiment conditions. However, the data do suggest that the use of real robots like humanoid robot NAO carries an advantage in terms of social presence that could provide educational benefits.	Kennedy et al., 2015
	Face: human instructor using a telepresence robot vs. autonomous social robot	MantraBot Classic, machine-like; Humanoid robot	**Cognitive** Credibility	Both the telepresence instructor (i.e., MantaroBot Classic) and the autonomous social robot teacher were rated by students (n=86) as “credible", however, students gave higher credibility ratings to the teacher as robot (i.e., telepresence robot) than robot as a teacher (i.e., autonomous social robot).	Edwards et al., 2016
	Animal-like (Paro) vs. human-like (iRobiQ)	Paro, zoomorphic; iRobiQ, humanoid	**Cognitive** Attitude, Robot roles	This study suggests that in addition to having an assistant teacher role, companion robots may have a useful comforting role. Both children (n=207) and teachers (n=22) expressed their positive attitudes about the robots and desire to have them in their schools. Participants wanted the robots to be more interactive, and perceived that the most useful functions were helping children with autism, comforting children in sick bay, and repeating exercises for children who need help.	Broadbent et al., 2018
	Teaching English and Physics	Lego-mindstorm in 3 different forms (i.e., machine-like, humanoid, zoomorphic)	**Behavioral** Active response and engagement **Cognitive** Preference: Robot likability, Trust, Satisfaction	In a lab experiment (n=108) with students from three different cultures (Germany, Korea, China), an effect of interaction performance (active response and engagement) and preference (likeability, trust and satisfaction) in the human-robot interaction was found. A robot’s anthropomorphic appearance increased likeability in all contexts. Compared with German participants, Chinese and Korean participants perceived the sociable robots to be more likeable, trustworthy and satisfactory, and they had higher engagement with the robot.	Li et al., 2010 (*article also in retail and arts & entertainment context*)
	Low expertise (receiving guests at a hotel front desk) vs. high expertise (tutoring)	Five types of humanoid robots less or more resembling humans	**Affective** Favorability **Cognitive** Trust	The results of the scenario-based experiment with an online panel of adults (n=505) show that affective and cognitive responses were more positive for the high-expertise humanoid (tutoring) than for the low-expertise humanoid (hotel reception) in all stages of the Uncanny Valley Theory except for the last stage, where the humanoid’s face is the same as a human’s face.	Jung et al., 2021 (*article also in hospitality contexts*)

	Puppet-like (Patricc) vs. humanoid (NAO)	Patricc, puppet-like; NAO, humanoid	**Cognitive** Learning, Interaction preference	The results of this longitudinal study indicate that there were no differences in learning outcome of children (n=9) in two robot conditions. An overwhelming majority of children, however, preferred interacting with the humanoid robot (NAO).	Levinson et al., 2020

Elderly Care *Antecedents / Service Settings*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Robot Morphology	**Zoomorphic** Interactive, animal-like behaviors (purring); life simulation (heartbeat)	Paro, Joy Dog, Joy Cat, Miro, Pleo, Perfect Petzz Dog, Furby, Hedgehog	**Cognitive** Design criteria	The study suggests significant differences in design preferences between older adults (n=17) and roboticists (n=18). Older people desired soft, furry, interactive animals that were familiar and realistic, while unfamiliar forms were perceived as infantilizing. By contrast, most roboticists eschewed familiar and realistic designs, thinking unfamiliar forms better suited older people. These results call for a user-centered design approach during the development of social robots.	Bradwell et al., 2019
	Anthropomorphic Robot type (Android vs. Humanoid)	AILA, humanoid; HRP-4C, android	**Behavioral** Intent to work with robot **Cognitive** Trust, Preferred level of automation	The results of an experiment with formal caregivers (n=102) suggest that the robot appearance (Android vs. Humanoid) does not have a significant effect on trust. However, the trust in robots was significantly related to intention to work and preference of automation levels.	Erebak & Turgut, 2019
	Zoomorphic vs. Anthropomorphic Companion- vs. service-type robot	Companion (zoomorphic)- vs. service -type robot, humanoid	**Cognitive** Robot acceptance	The results of an experiment with older adults (n=33) show the higher level of acceptance of a human-like service-oriented robot compared to an animal-like companion-oriented robot.	Chu et al., 2019
	From machine-like to androids Companion- vs. service-type robot	83 different robot types	**Behavioral** Intention to use **Cognitive** Likeability, Uncanny valley effect	The results of the survey with 225 adults (younger (n=77, age 18–39 years), middle-aged (n=87, age 40–59 years), and older (n=91, age 60–87 years)) show that the Uncanny Valley Effect is present in younger and middle-aged adults; while older adults preferred humanlike over non-humanlike robots, regardless of robot function (companion vs. service type).	Tu et al., 2020a

Healthcare Antecedents / Service Setting		Robot Type	Consumer Outcomes	Key Findings	Authors
Physical + Verbal Medical Care Measuring blood pressure, talking to patients; Instructing games for physical exercise	**Robot morphology** Human-likeness	Peoplebot, machine-like	**Affective** Blood pressure**,** Emotional experiences (PANAS)	Participants (n=57; 40 years old and older) were asked to draw robots. When the robot (*Peoplebot*, non-humanoid telepresence robot) is introduced, increasing in blood pressure and negative emotions is greater in the participants who had drawn a human-like robot and thus have a tendency to anthropomorphize than those who had drawn a box-like robot.	Broadbent et al., 2011
			Cognitive Mind perception, Perceived eeriness, Perceived robot, Personality	Results of this lab experiment (n=30) show that human-likeness of robot faces displayed on *Peoplebot* (non-humanoid telepresence robot) increase participants' attribution of mind and positive personality attribution. Eeriness was associated with positive personality attribution to the robot but not associated with human-likeness.	Broadbent et al., 2013
	Robot morphology Humanoid robot vs. tablet	Pepper, humanoid	**Behavioral** Willingness to keep on exercising measured by the dropout rates **Cognitive** Motivation, Trust	In a longitudinal field experiment (n=24), researchers found that participants in both groups reported that this rehabilitation platform (robot or tablet) addressed their arm rehabilitation needs, and they expressed their desire to continue training with it even after the study ended. Further, the study found a trend for higher acceptance of the system by the participants in the robot group; however, this difference was not significant; system failures did not affect the long-term trust that users felt towards the system.	Feingold-Polak et al., 2021
Verbal Medical Care Delivering health message Delivering medicine	**Embodiment** (Robot Present vs. Robot Projected (Software Agent)); **(**Robot vs. Tablet)	iRobiQ, humanoid	**Affective** Blood pressure, Heart rate, Enjoyment **Cognitive** Robot attitude, Trust, Robot personality	Participants (n=65) in a lab experiment perceive healthcare instructions more positive and their participation in exercises is higher in the robot (*iRobiQ, humanoid*) than in the computer tablet condition, Degrees of trust, enjoyment, and desire for future interaction are also higher in robot than in the tablet condition.	Mann et al., 2015
		Nursebot, humanoid	**Affective** Emotional experiences, (Enjoyment, Mood) **Behavioral** Engagement, Disclosure of undesirable behavior, Eating behavior **Cognitive** Robot lifelikeness, Robot personality	In the embodied robot condition with humanoid robot *Nursebot*, engagement of the participants (n=113) was higher, and the disclosure of undesirable behaviors lower compared to the robot-like software agent condition. Participants took in the least calories and anthropomorphized most with the collocated robot.	Kiesler et al., 2008

Domestic Services *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Anthropomorphic vs. Machine-like/Object-based	Robot appearance: (1) Humanoid (2) Mechanoid (3) Basic	Peoplebot, machine-like	**Cognitive** Preference	Overall, participants (n=79) tended to prefer robots with more human-like appearance and attributes. Introverts and participants with lower emotional stability tended to prefer the mechanical looking appearance to a greater degree than other participants.	Walters et al., 2008
	Different levels of human-like appearance: (1) human face (2) robot face (3) mix between human and robot face	Pearl Nursebot, Nexi MDS (Mobile/ Dextrous/ Social), NAO, and Kobian, humaoid	**Affective** Anxiety **Cognitive** Perceived usefulness, likeability, Trust	The results of the experiment with younger adults (n=32) and older adults (n=32) indicated that people's perceptions of robot faces vary as a function of robot human-likeness. In general, people perceived a mixed human–robot appearance less favorably compared to highly human and more robotic appearance. Additionally, the nature of the task also influenced people's overall perceptions of robots. Robots were most positively evaluated for assistance with chores and less positively for personal care and decision-making.	Prakash & Rogers, 2015
	Organism- (i.e., humanlike) vs. Object-based robot design	NAO HangulBot Pepper, humanoid, object-like	**Behavioral** Purchase intention & willingness to pay **Cognitive** Robot evaluation & Acceptance, Familiarity	The results of the study (n=52) show that robot design plays an essential role in the consumers' acceptance of robots. Specifically, object-based robots were accepted more by consumers than organism-based robots in our study, although organism-based robots were perceived as more familiar than object-based robots. These results show that the higher perception of familiarity by consumers may not necessarily lead to a higher acceptance of robots by consumers.	Kwak et al., 2017
Humanoid vs. Android	Designed to be a friend or member of the family, offering assistance through social interaction	Repliee, android and Robovie, humanoid	**Cognitive** Participants impressions of robot, Humanness, Likeability, Friendliness	The results of the scenario-based experiment with students (n=19) suggest participants' willingness to attribute human roles and tasks to an android, although they did not indicate an overall preference for the robot as a social actor. Participants further indicate that female household robots evoke feelings of safety, however, stereotypical gender roles might lead to negative evaluations of female, android domestic robots.	Carpenter et al., 2009
Tall vs. short robot	Designed as a household assistant	TiaGo, humanoid in two different heights	**Behavioral** Proximity to robot in t1 and t2 **Cognitive** Initial learned trust, Dynamic learned trust, Negative attitudes towards robots	In lab experiment (n=28) participants were approached by a humanoid domestic robot two times and indicated their comfort distance and trust. Regardless the size of the robot, the results favored the differentiation and interdependence of dispositional, initial, and dynamic learned trust layers. The findings underline the meaningfulness of user characteristics as predictors for the initial approach to robots and the importance of considering users' individual learning history regarding technology and robots.	Miller et al., 2021
Embodiment 2D vs. 3D vs. VR vs. embodied /live)	Designed as a Personal Assistant	Roboy, humanoid	**Behavioral** Purchase intentions **Cognitive**	In a mixed method study with field and video-based experiments (n=119) results on perceived immediacy revealed that an HRI scene played live in front of the participants outperformed watching the same HRI scene on a screen. Interestingly, no significant difference in perceived immediacy was found between the live presentation	Mara et al., 2021

			Perceived immediacy, Human-likeness, Eeri-ness, Likability	and the presentation via VR headset. The only significant difference found was that the robot was assessed as more human-like in the live condition.	

Retail *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Retail (Chocolate store)	Robot vs. table at entrance of retail shop to attract customers	Pepper, humanoid Tablet PC	**Behavioral** Number of started interactions, Number of people attracted, Number of people entering the store, Number and time of transactions	The results of this field observation study (n=1336 observations) showed that the humanoid robot was more effective in eliciting interactions (i.e., passersby touching the screen) than the tablet PC and that these interactions lasted longer (almost 50%); more people looked at the store and consequently entered it when the social robot was deployed. The study also found that participants spent more money during the days when the humanoid social robot was present in front of the store.	Brengman et al., 2021

Table E1.3. Summary of key insights from design theme: Behavior (software) and appearance (hardware) in one study

Hospitality & Tourism *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assistive Services	**Restaurant/Bar** Service failure in restaurant setting	NAO, humanoid; CareOBot, mechanical	**Behavioral** Behavioral intention **Cognitive** Satisfaction	In four scenario- or video-based experiments (n=205; n=205; n=189; n= 212) results revealed that consumers will be less satisfied when a process failure is caused by a humanoid than by a nonhumanoid, mediated by lower warmth perceptions; such differences will not emerge for an outcome failure. Further, consumers will be more satisfied when a humanoid delivers an apology (vs. control) as a service recovery following a process failure, mediated by higher warmth perceptions. Moreover, consumers will be more satisfied when a humanoid delivers an explanation (vs. control) as a service recovery following a process failure, mediated by higher warmth perceptions. Lastly, consumers will be more satisfied with service recovery when an apology is given by a human employee (vs. by a nonhumanoid only); the positive effect of a human intervention will be attenuated for a humanoid.	Choi et al., 2021a
	Restaurant Delivery robot appearance, voice and language (humanlike vs. machinelike)	Delivery robot T1, Amy, humanoid and machinelike	**Behavioral** Revisit and WOM intentions **Cognitive** Service encounter evaluation	According to the results of this experimental study (n=587), humanlike voice is a more dominant factor that affects consumer outcomes compared to language and appearance. Humanlike language has also effects, especially on the service encounter evaluation. Compared to language and voice, physical appearance of robot has minimal effects on consumer outcomes. Positive emotions mediate the relationship between voice, language, and consumer outcomes. Perceived credibility only mediates language effects on consumer outcomes.	Lu et al., 2021
	Restaurant/Bar Waiter tasks (e.g., taking orders, providing meal advice)	K5, mechanical; HRP-4, humanoid; Geminoid, android	**Behavioral** Loyalty intentions	The results of a picture-based experiment (n=526) revealed that human-likeness positively affects four dimensions of service value expectations and subsequently their loyalty intention. Perceived competence of the robot influences mainly utilitarian expectations (i.e., functional, and monetary value), while perceived warmth influences relational expectations (i.e., emotional value). Interestingly, and contrary to theoretical predictions, the influence of the robot's warmth on service value expectations is more pronounced for customers with a lower need for social interaction.	Belanche et al., 2021
Socially Interactive Services	**Hotel** Check in desk	Pepper, humanoid; Sophia, android	**Behavioral** Responses (Word-of-mouth) **Cognitive** Satisfaction	Three video-based experimental studies (n=350; n=219, n=22) revealed that customers with low (vs. high) scores on anxious attachment style (AAS) measure respond more negatively to frontline service robot (compared to a frontline human agent). The researchers investigated alternative explanations for these findings, such as robots' level of anthropomorphism. The study showed that human-likeness features such as voice type and level of human-like physical appearance, cannot explain our findings. The results indicate that for low-anxious-attachment style	Pozharliev et al., 2021a

				(AAS) customers replacing frontline human service agent with frontline robot undermines customer attitude and behavioral responses to service robots, leading to possible implications on customer segmentation, targeting, and marketing communication.	
	Theme Park Various roles and functions in theme parks (e.g., greeting, information providing, enjoying, assisting visitors)	Various, Humanoid, cartoonlike, zoomorphic, anime	**Behavioral** Customer loyalty	According to this survey about theme park visitors (n=385), there is a positive relationship between robot functionalities and customer loyalty. This relationship is stronger when the robot is anthropomorphic.	Milman et al., 2020
	Hotel Various socially assistive and interactive roles including check-in, greeting, advising, carrying, helping, room service. Robot evaluation (safety, scalability, autonomy, imitation, privacy)	Various, humanoid and anthropomorphi c	**Behavioral** Behavioral intention **Cognitive** Attitude, Satisfaction	This online experiment (n=304) shows that user satisfaction with robots had a positive impact on hotel satisfaction and room purchase intention. Compared to high human-likeness, consumers are more likely to accept medium level human likeness.	Jia et al., 2021

Elderly Care		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Antecedents / Service Setting					
Medicine delivery and medical message	**Robot Morphology** (Robot with abstract or human-like face) **Robot Voice** Synthesized vs digitized (human) voice messages, interactive behavior	Peoplebot, machine-like	**Affective** Heart Rate, Galvanic skin response **Cognitive** Perceptions of human-like appearance, Arousal, Valence	In this experiment (n=24) results indicated that participant physiological responses varied with events in their interaction with the robot. The different robot features had different utility for stimulating participant arousal and valence, as well as physiological responses. In general, results indicated that adding anthropomorphic and interactive features to service robots promoted positive emotional responses [increased excitement (GSR) and happiness (HR)] in elderly users.	Zhang et al., 2010
Physical exercise	**Robot Morphology** (Humanoid vs. Machine-like)	NAO, humanoid Poppy, machine-like	**Affective** Heart rate **Behavioral**	The results of a lab experiment with elderly (n=32) showed that the robots motivated the older adults to engage more in physical exercises while the type and timing of feedback influenced this engagement. Most of the participants found the system useful and easy to use, had a positive attitude towards the system and noted	Avioz-Sarig et al., 2021

	Type and timing of feedback		Intention to use, Reaction time, Engagement (Eye contact duration with robot, Completed exercises) **Cognitive** Attitudes, Acceptance	their intention to use it. Most users preferred the more mechanical looking robot (Poppy) over the humanoid/toy-like (NAO).	
Cognitive exercise	**Robot Morphology** (Humanoid robot vs. tablet) Type of feedback	Pepper, humanoid	**Behavioral:** Engagement (Participants talked to the robot and touched it as if it was a social entity, enthusiasm **Cognitive:** Satisfaction with training and user enthusiasm rated by caregivers	The results of a lab experiment with 14 elderlies showed that the robot vs. the tablet was received with more enthusiasm by the older adults which improved their level of engagement. The provision of a digital game through a humanoid robot seems to successfully stimulate older adults with mild cognitive impairments in better committing to their training and engaging with the robot throughout its entire duration, especially when the robots gave more empathic feedback.	Manca et al., 2021

Healthcare		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Antecedents / Service Setting					
Verbal Medical Assistance Delivering medical message	**Robot Morphology** (Humanoid vs. Machine-like) **Message Frame** (Etiquette Strategies: Control, Positive, Negative, Mixed)	Peoplebot, machine-like	**Behavioral** Task performance (Completion of puzzle and response time) **Cognitive** Perceived etiquette strategy (Relative disruptiveness, Message length, Politeness, usefulness, Ease of understanding, Tfrustworthiness)	Usage of positive language (complimenting participants) by machine-like robots (*Peoplebot*) did not enhance participants' (n=32) perceived etiquette scores. Negative etiquette strategies (apologizing) by robots improve task performance (in terms of user response time to robot requests for medicine intake) of participants and increase the level of perceived etiquette strategy.	Zhu & Kaber, 2012
Verbal + Physical Medical Assistance/Care Medical Coaching; Gymnastic Instructions for Physiotherapy	**Robot Morphology** (Aesthetic, Realism) **Robot Efficiency** (Perceived Affordances)	LegoStorm, machine-like	**Cognitive** Use intentions, Involvement, Distance	Results of a lab experiment with three different machine-like LegoStorm robots indicate that (n=29, students), perceived realism of and aesthetics of social robots plays a very limited role in use intention, interaction with robots and engagement of participants in a physiotherapy context. Perceived affordances improve user use intentions and engagement.	Paauwe et al., 2015

Domestic Services *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assisted living services	Robot cook	Various forms of social robots (mechanical, humanoid, android (male/female))	**Cognitive** Liking, Compatibility, Purchase intention	In this scenario-based study (n=953), findings indicated that while consumers prefer higher levels of humanness and moderate-to-high levels of social interaction opportunity, only some participants liked robots more when dialogue (high-interaction opportunity) was offered. The researchers propose the Humanized-AI Social Interactivity Framework which extends previous studies in marketing and consumer behavior literature by offering an increased understanding of how households will choose to interact with service robots in domestic environments based on humanness and social interaction.	Letheren et al., 2021

Public Services *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Security	Identity card control: Robot introduces its detailed functions and checks the participant's student identity card.	Legomindstorm in 3 different forms (i.e., machine-like, humanoid, zoomorphic)	**Behavioral** Active response & engagement **Cognitive** Preference: Robot likability, Trust, Satisfaction	In a lab experiment (n=108) with students from three different cultures (Germany, Korea, China), an effect of interaction performance (active response and engagement) and preference (likeability, trust and satisfaction) in the human-robot interaction was found. Results also indicated that the machine-like robot was most suitable for the security guard task, which agrees well with the findings from previous studies. A robots' anthropomorphic appearance increased likeability in all contexts. Compared with German participants, Chinese and Korean participants perceived the sociable robots to be more likeable, trustworthy and satisfactory, and they had higher engagement with the robot.	Li et al., 2010 *(article also in education and arts & entertainment context)*
Public Services	Robots provide blessings to believers with different morphology, voice and different bible verses	BlessU2; machine-like; QT, humanoid/cartoon-like	**Affective** Emotions (Positive: Desire, Satisfaction, Pride, Hope, Joy, Fascination, Admiration; Negative: Disgust, Dissatisfaction, Shame, Fear, Sadness, Boredom) **Cognitive**	In a qualitative study (n=1923 comments after interacting with BlessU robot) and a scenario-based experiment (n=41) researchers found that most comments were positive (51%), many neutral (29%) and some negative (20%). Moreover, the preferable scenarios for religious robots were: to demonstrate human creativity, to increase the reach of religious institutions and personnel, to offer service when there is no alternative, and to enhance service with unique robot capabilities. In the second study, the results revealed that a varied appearance, behavior, and functionality of the blessing robot, does not make any difference in users' evaluation of the robot. Still, the qualitative comments revealed strong preferences towards a specific set of characteristics which are discussed.	Löffler et al., 2021

		Scenarios for robot implementation, Anthropomorphism			

Retail		Robot Type	Consumer Outcomes	Key Findings	Authors
Antecedents / Service Setting					
Retail Shopping Mall & Stores	Promotional activities by small and human-sized robot; recommendation by robots	Robovie-II & Robovie-miniR2, humanoid	**Behavioral** User engagement (Taking coupon from robot)	The field trial (n=249) with humanoid robots *Robovie_II* (normal-sized) and *Robovie-miniR2* (small) shows that a small robot increased the number of people who printed coupons more than a normal-sized robot. The number of people who printed coupons also increased when the robot asked visitors to freely select from all coupon candidates or to listen to its recommendation.	Shiomi et al., 2013

Table E2. Summary of key insights from HRSI studies under the **delegate theme**

Hospitality & Tourism — *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assistive and Socially Interactive Services	**Hotel** Service delivery (e.g., room service, greeting, check-in) human vs. robot	Various humanoid robots	**Cognitive** Service & interaction quality	Focus groups (n=11) and an online survey (n=400) reveal that in terms of interaction quality, human staff performed best and provided customers with better sympathetic care, pleasant and friendly services than with various humanoid service robots only or with their combined services. Customers perceived that human staff are better equipped with the knowledge to answer their questions and exhibit better communication skills to make them feel comfortable than robots do.	Choi et al., 2019b
		Mobile service robot, machine-like	**Cognitive** Brand Experience	Results of video-based experiments (n=60; n=180) suggest that sensory and intellectual experiences were reported higher while affective experiences were reported lower in robotic compared to human room services; service with a machine-like robot led to higher rating of behavioral experience in midscale and budget hotels, but not for luxury hotels.	Chan & Tung, 2019
		Unnamed, humanoid	**Cognitive** Deceiving intent, Blame for lying	Results of a scenario-based study (n=399) revealed that the folk concept of lying applies to artificial agents in just the same way as it does to human agents. Crucially, what matters for lying is not actual deception, but the perceived intention to deceive of robots and humans alike.	Kneer, 2021
		Pepper, humanoid	**Affective** Heart rate variability	The results of this lab experiment (n=116) using a VR and biosensors revealed that consumers with low (vs. high) scores on anxious attachment style measures show a decrease in automatic emotional response (heart rate variability).	Pozharliev et al., 2021b
	Hotel Service recovery entity (Robot-generated text vs. Robot-generated voice vs. Human service employee)	Pepper, humanoid	**Cognitive** Recovery, Satisfaction, Perceived sincerity	In this online experiment (n=248), results revealed that service recovery provided by a human is perceived as sincerer and more satisfactory than provided by a service robot. Need for human interaction pronounce this effect. There is no difference between the use of service robots with text-based service recovery and voice-based service recovery (apology).	Hu et al., 2021
	Hotel Reception desk (humanoid vs. self-service machine) Presence vs. absence of human staff	Humanoid	**Behavioral** Willingness to pay, Visit intention	Results of four experimental studies (total n=1641) revealed positive effects of anthropomorphizing service robots, positively affects for service quality and first-visit intention. Presence of human staff negates humanoid robot's (vs. self-service machine's) indirect effects on expected service quality via warmth and competence while consumers' need for human interaction is controlled for. Additionally, the results showed that a humanoid robot's effect on expected service quality is positive for all but there are low technology readiness levels.	Yoganathan et al., 2021

	Airport/Restaurant/Bar Check-in, restaurant experience, *life insurance Human vs. human & robot vs. robot vs. self-service	Pepper, humanoid, Self-service Machine, machine-like	**Behavioral** Brand usage intent **Cognitive** Service experience	In two photo-based, scenario experiments (n=563; n=400) it was found that augmenting or substituting human employees with frontline service robots (FLSRs) has positive and negative consequences irrespective of value creation model, AI type, and service type (i.e., experience-restaurant vs. credence-insurance). Further, FLSRs increase the feeling of innovativeness of customer service. Also, if human employees are replaced by FLSRs, they damage the ethical/societal reputation of the service provider in terms of both service experience and brand usage intent. Moreover, personal customer characteristics (openness-to-change and preference for ethical/responsible service providers) moderate these effects. In that, some consumers value innovativeness more, others appreciate the fact that a service provider is responsible for employees and society.	McLeay et al., 2021
Assistive Services	**Restaurant** Human vs. android robot serving food in a restaurant Human vs. humanoid robot greeting and seating in a restaurant	Android, humanoid robot	**Behavioral** Compensatory consumption (Caloric intake selected, Chocolate cake consumption intentions)	In a photo-based (n=100) experiment with an android robot, it was found that the robot triggers greater feelings of eeriness and identity threat, which leads consumers to cope through selecting more calories. In a video-based (n=180) experiment with a humanoid robot vs. a human server in a restaurant setting, participants showed more chocolate cake consumption intentions with a robot (vs. a human), thus showing compensatory consumption behavior. When the food is positioned as healthy, the effect is attenuated. Participants ate more food with a robot with a human name than with a robot with a mechanical name.	Mende et al., 2019 *(Study 2 and 3a; article also in healthcare context)*
	Hotel/Restaurant Human vs. robot hotel reception and restaurant waiter; service failure vs. success	Pepper, humanoid	**Cognitive** Attributions of responsibility	In two vignette-based experiments (n=331; n=229), results indicate that participants make stronger attributions of responsibility for the service performance toward humans than toward robots, especially when a service failure occurs. Thus, responsibility is attributed to the firm rather than the frontline robot. The perceived stability of the performance is greater when the service is conducted by a robot (vs. a human). The results imply that customers expect employees to shape up after a poor service encounter but expect little improvement in robots' performance over time.	Belanche et al., 2020
	Restaurant Robotic cook	Type of social robot not specified	**Cognitive** Responsibility attribution to service provider, Responsibility attribution to service firm	The results of three scenario-based experiments (n=200; n=100; n=207) showed that people attributed less responsibility toward a robot than a human for the service failure because people perceive robots to have less controllability over the task. Still, consumers attributed more responsibility toward a service firm when a robot delivered a failed service than when a human delivered the same failed service.	Leo & Huh, 2020 *(article also in healthcare context)*

Education		Robot Type	Consumer Outcomes	Key Findings	Authors
Antecedents / Service Settings					
Human vs. Robot Educa-tional approach	Human vs. robot peer group providing incorrect visual or verbal judgement	NAO, humanoid	**Behavioral** Linguistic imitation	The results of the experiment (n=78) demonstrate that morphological conformity through linguistic imitation occurs, but that it is socially constrained—it happens with human peers but not with NAO robot peers.	Beckner et al., 2016
	Social interactivity Robot high vs. low on social interactivity vs. human	Pepper, human-oid	**Cognitive** Learning	The results of the experiment indicate that the student's (n=46) verbal comprehension was comparable in human- and Pepper robot- lecturer scenarios when the question difficulty was high. However, for easy questions, the performance of students in the robot scenarios was significantly inferior to that of students in the human lecturer scenario.	Palanica et al., 2019
Human vs. Robot with Focus on Educational task, Individ-ual, or Situa-tional ante-cedents	Human vs. robot reading companion	Robot Julia, hu-manoid	**Behavioral** Desire to interact **Cognitive** Learning, Perceptions	The results of the experiment with elementary school children (n=36) show that children's reading comprehension was not significantly different between human and robot conditions. However, children perceived the robot companion (Robot Julia) as more favorable and desirable to read with than a human co-reader.	Yueh et al., 2020
	Age groups	Baxter, human-oid	**Cognitive** Attitude	The experiment with students (n=190) suggests that the age of learners is the main factor influencing their attitudes towards an education robot (i.e., Baxter robot).	Fernández-Llamas et al., 2018
	Classroom with vs. without robot	Humanoid robot with zoomor-phic features	**Cognitive** Learning	Both quantitative and qualitative findings of this study indicate that the students' (n=64) English learning experiences were enhanced, as were their motivation and learning outcomes as a result of interacting with various educational robot designs.	Wu et al., 2015
	Agency (human teacher vs. robot teacher)	Baxter, human-oid	**Cognitive** Learning	The field experiment with students (n=210) found no difference in learning outcomes between human and robot teacher groups. However, age had moderating effects. Older students performed better when taught by a robot.	Fernández-Llamas et al., 2020
	Human vs. robot tutor; robot tutor on one vs. two occasions	NAO, humanoid	**Affective** Enjoyment, Surprise **Cognitive** Learning	Results of field experiments with students (n=138; n=89; n=78) show that those who were tutored by a robot-tutor for the first time had higher level of enjoyment and surprise, but lower learning outcomes compared to students taught by a human-tutor. When students were lectured by a robot-tutor for the second time, they had higher level of acquired knowledge and enjoyment and a drop in expressed surprise, compared to both, one human-tutor lecture and one robot-tutor lecture or one robot-tutor lecture.	Velentza et al., 2021
	Human vs. robot tutor, attitudes towards robots (NARS), anxiety, personal traits		**Cognitive** Learning	Results of the field experiment with students (n=102) show that negative attitudes towards robots and anxiety about learning a second language impeded participants from learning vocabulary in the robot tutor	Kanero et al., 2022

				condition whereas the personality trait of extroversion negatively predicted vocabulary learning in the human tutor condition.	
	Human vs. robot professor		**Behavioral** Class performance **Cognitive** Platform usability	Field experiments with high-school students (n=140) demonstrate that the implementation of a robotic platform improves the class's dynamism and the cooperative behavior of the students, by following the Octalysis approach.	Reyes et al., 2021

Elderly Care *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Human vs. Robot in Assisted Living Services	Domestic services: navigation, grasping, manipulating, and delivering objects, opening doors, folding towels	PR2 – humanoid domestic robot	**Cognitive** Opinions about robots, Preference, Robot acceptance	The focus group findings suggest that the older adults (n=20) were generally open to robot assistance but were discriminating in their acceptance of assistance for different tasks. They preferred robot assistance over human assistance for tasks related to chores, manipulating objects, and information management. In contrast, they preferred human assistance to robot assistance for tasks related to personal care and leisure activities.	Smarr et al., 2014
Human vs. Robot in Socially Assistive Services	Escorting elderly to the playground, providing instruction on physical exercise, motivating and providing progress feedback	Vizzy, humanoid	**Cognitive** Automated social presence, Social cognition	The results of the experiment with elderly people (n=58) show that Vizzy activated feelings of automated social presence (i.e., feeling of being in a presence of another social entity). Furthermore, when compared to a human coach, Vizzy scored lower on perceived warmth and perceived competence, which further affected elderly people's experience (i.e., emotional and cognitive reactions and behavioral intentions) towards physical activity.	Čaić et al., 2020
	Conducting a singing group as group therapy for elderly	Zenbo, Cartoon-like	**Behavioral** Imitative behavior **Cognitive** Altruism, Group cohesiveness, Universality, Interpersonal learning, Development of socialization techniques, Imparting of information, Catharsis, Corrective recapitulation of primary family group, Self-understanding, Instillation of hope, Existential factors	This longitudinal field study (n=14) showed that the robot-directed singing therapy sessions effect on therapeutic factors in week 8 were higher than or equal to those in week 4 in 11 of the 12 therapeutic factors. Thus, participants' acceptance of the robot seemed to increase during the process. However, a significant difference could only be shown for "interpersonal learning".	Liao et al., 2021

Healthcare *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Physical + Verbal Medical Assistance Interacting with children before and during intravenous line placement;	**Human vs. Robot** (Human medical professional vs. robot)	NAO, humaoid	**Affective** Pain, Fear (Before, During insertion) **Behavioral** Additional pain medicine	In a field experiment (n=119), no significant differences were found between groups and there were no changes over time for pain or fear. However, exploratory analyses showed that patients in the NAO group were 5.04 times more likely to complete intravenous induction, compared to the care professional group.	Lee-Krueger et al., 2021
Talking with children, asking questions, playing with toys during vaccination			**Affective** Perceived pain and distress **Behavioral** Avoidance behavior of children during flu vaccination	In parent, child, nurse and researcher ratings, children's (n=57) interaction with humanoid robot *NAO* decreased pain and distress in children during flu vaccination.	Beran et al., 2013
Verbal Medical Assistance Taking Medical History	**Human vs. Robot** (Human Clinician vs. Robot Clinician);		**Affective** Self-reported emotions, Physiological arousal **Behavioral** Attention, Gaze behavior **Cognitive** Cognitive performance, Workload	In a lab experiment in which a cognitive assessment was conducted either by humanoid robot NAO or a human clinician no difference in participants' (n=29) self-reported emotions, cognitive performances, workload, and physiological arousals were found. However, attention and gaze are higher in interacting with the robot than with the human examiner.	Desideri et al., 2019
Physical Medical Assistance Measuring blood pressure and heart rate; take temperature, pulse, and blood pressure	(Medical Student vs Robot);	Peoplebot, machine-like	**Affective** Blood pressure, Heart rate, Emotions **Cognitive** Quality of interaction and experience	Results of a survey and a lab experiment show that participants (n=57) show no difference in blood pressure when it is measured by a medical student or an anthropomorphized, machine-like robot (*Peoplebot*). However, participants report lower comfort and accuracy ratings in the robot condition. Emotions and attitudes towards robots predict perceived quality of interaction and experience.	Broadbent et al., 2010
	(Human vs. Robot)	Humanoid robot	**Behavioral** Status consumption: high price vs. low price water	In a video-based experiment (n=80), participants were more likely to choose the premium (vs. generic) product after an interaction scenario in a healthcare setting with a humanoid robot than a human.	Mende et al., 2019 *(study 1a; article also in hospitality context)*

Physical + Verbal Medical Care Eye control	**Role of Robot** (Caregiver vs. Care recipient in ophthalmology context)	NAO, humanoid	**Cognitive** Trust, Human-likeness, Intelligence, Feel of social presence, Enjoyment, Relationship satisfaction	Results of a lab experiment with humanoid robot *NAO* show that receiving care from a robot leads participants (n=60) to develop more positive perceptions towards the robot compared to being in the role of the caregiver for the robot. The effect of the caregiving role on the relationship satisfaction with and trust towards the robot is mediated by perceived benefit. The effects of the caregiving role on perceived human-likeness and perceived intelligence are mediated by social presence.	Kim et al., 2013
Verbal Medical Care Medical Consultancy Pharmacy	**Human vs. Robot** **Robot Communication** (Health Message Type and Frame)	Alice R50, humanoid	**Cognitive** Doctor evaluation, Message evaluation, Medical adherence, Expected quality of life, Perceived ethics, Perceived affordances	Results of a video-based experiment show that participants' (n=134) evaluations of medical services are better in the robot doctor (*Alice R50, humanoid*) compared to the human doctor condition. No difference in the level of expected quality of life was found. The robot is perceived as an ethical and skilled agent, and use intentions are positive.	Hoorn & Winter, 2018
	Human vs. robot in embarrassing service encounter	Pepper, humanoid	**Cognitive** Consumers' anticipated embarrassment	In three studies which included in-depth interviews and two lab experiments (n=40; n=166; n=121), results showed that interactions with service robots attenuated customers' anticipated embarrassment. Study 1 identified factors that can reduce embarrassment including the perception that service robots have reduced agency and emotions. Study 2 revealed that people feel less embarrassed during a potentially embarrassing encounter when interacting with service robots compared to frontline employees. Study 3 revealed the mediating effect of perceived agency, but not emotion, of frontline counterparty effects on anticipated embarrassment.	Pitardi et al., 2022
	Human vs. Robot pharmacist preparing medication	Type of social robot not specified	**Cognitive** Responsibility attribution to service provider, Responsibility attribution to service firm	The results of three scenario-based experiments (n=200; n=100; n=207) showed that people attributed less responsibility toward a robot than a human for the service failure because people perceive robots to have less controllability over the task. Still, consumers attributed more responsibility toward a service firm when a robot delivered a failed service than when a human delivered the same failed service.	Leo & Huh, 2020 *(article also in hospitality context)*

Domestic Services Antecedents / Service Setting		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assisted living services	Assistance in the kitchen	Pepper, humanoid	**Cognitive** Intentionality, Controllability, Desirability of the behaviors	The results of the experiment with students (n=90) show little variation in participants' overall judgment of human vs. humanoid behavior in the kitchen. Results indicate: substantially similar judgments of human and robot behavior, both in terms of (1a) ascriptions of intentionality/controllability/desirability and in terms of (1b) plausibility judgments of behavior explanations; (2a) high level of agreement in judgments of robot behavior – (2b) slightly lower but still largely similar to agreement over human behaviors; (3) systematic differences in judgments concerning the plausibility of goals and dispositions as explanations of human vs. humanoid behavior.	Thellman et al., 2017

Public Services Antecedents / Service Setting		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Public Services (Train station)	Human vs. human wearing a mascot costume vs. robot perform dull (guidance), stressful (dealing with complaints) and dirty tasks (lost items in trash) in a city mall environment	Robovie, humanoid	**Cognitive** Human-likeness, Appropriateness	In a video-based study with humanoid robot *Robovie* (n=30), results show that people prefer to have a robot rather than a human perform these troublesome tasks, even though they require much communication with people. Not surprisingly, humans were rated higher in terms of human-likeness of appearance and behavior, cognitive human-likeness and human-likeness for human rights followed by the costumed human and the robot.	Hayashi et al., 2012
Security/Peacekeeping	Delivering risk messages (i.e., bad weather) to people in hardly-reach areas; Human vs. social robot delivery; language style imperative vs. declarative	BEAM, 5machine-like	**Behavioral** User engagement (Retention of Message; Behavioral intentions, Interpersonal social presence)	In a laboratory experiment with social robotic platform *BEAM* the authors find that those participants (n=146) seem to ruminate on the visual stimuli or the content delivery medium rather than focusing on the content of the message - the robot served as a technological distractor. Higher levels of social presence with the robot are negatively related to message retention. The social robot does not seem to induce any difference in reported behavioral intentions, as neither did the message manipulation.	Rainear et al., 2019

Table E3. Summary of key insights from HRSI studies under the **deploy theme**

Hospitality & Tourism *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Assistive and Socially Interactive Services	**Hotel** Robot embodiment, activity of the robot, communication initiation	Saccarino, humanoid	**Cognitive** User engagement, Comfort	In a field trial interacting with humanoid bellboy robot (*Saccarino*), users (n=95) tend to maintain a personal distance when interacting; embodiment, a greeting model and active looking engages users in maintaining longer interactions with the robot.	Rodriguez-Lizundia et al., 2015
	Hotel Application of robot in hotel lobby: greeting, information providing, taxi call, videoconferencing, accompanying guests, breakfast control	Saccarino, humanoid	**Behavioral** Engagement and interaction with robot	In this longitudinal field experiment covering over 350 user interactions with humanoid bellboy robot *Saccarino* in a Spanish Novotel hotel, researchers found interactions increased on weekends. Children and older adults get closer to the robot during interactions and seem more comfortable with it than middle-aged adults. Users do not seem comfortable when talking loudly to a robot in the presence of other people and/or they feel they do not know how to talk to it. Saccarino being in the *awake status* and taking the initiative for interaction favored user engagement. Over 50% of the requested information concerned Saccarino itself, followed by information about the hotel facilities and the weather forecast. Entertainment options were used least.	Pinillos et al., 2016
	Hotel Robot embodiment and perception of human-orientation in service delivery	Various robot types: humanoid, zoomorphic, machine-like	**Cognitive** User experience	Thematic analysis of text reviews from social media of various robot types (humanoid, zoomorphic, machine-like) in hotels reveals that users and robots can co-create novel experiences, with some guests even proactively seeking new opportunities to interact and communicate with robots to develop a certain level of "relationship" with them.	Tung & Au, 2018
	Hotel Customer reviews of service delivered by robots in robot-staffed hotels in Japan	Various (humanoid, zoomorphic and mechanical)	**Cognitive** Perception of robotic service, Satisfaction	In a study using secondary data from hotel reviews, it was found that HRI may become more salient in the memory of Japanese than in non-Japanese tourists. Japanese and non-Japanese reviews used different formulations to describe the experience of HRI. The Japanese reviews tended to express more emotional responses to HRI, whereas the non-Japanese reviews frequently described the functional and technical aspects of robot-provided services. However, the overall satisfaction score for robot-staffed hotels was significantly lower in the Japanese than in the non-Japanese reviews.	Choi et al., 2021b

Restaurant/Bar Machine-like robot delivering food	Machine-like robot	**Behavioral** Intention to use robots in restaurants	In a scenario-based survey (n=420), results show that hedonically motivated consumer innovativeness and socially motivated consumer innovativeness have positive effects on attitude and are enhanced by attractiveness, utility, subcultural appeal, and originality. The results reveal that sensory elements of robot services improve customer attitudes towards the use of robots in restaurants.	Cha, 2020
Hotel Application of robot as a receptionist	Pepper, humanoid	**Cognitive** Customers' attitude, Willingness to talk with a machine, Situations in which customers prefer to be assisted by the robot and by humans, Ease of interaction, Satisfaction, Level of customers' awareness about the robot/AI, Past experiences with such technology	In a field study (semi structured interviews (n=12), participant interaction observations (n=65), questionnaires (n=30), data analysis of Pepper's data collection) revealed that Pepper can act as an augmentation force and that FLEs' role can evolve mainly into that of enabler - of the customers and of technology -, innovator and coordinator, while customers may take above all the role of enabler of the technology. Moreover, the study introduces a new FLE role of "AI supervisor".	Mingotto et al., 2021
Hotel Application of a robot as concierge in a university lobby to test the role of social presence		**Behavioral** Intention to use robots	Social presence perceptions of consumers (n=180), who are engaged with Pepper in a business school lobby, is indirectly and positively related with robot use intentions through trust, usefulness, and emotional appeal.	Etemad-Sajadi & Sturman, 2022
Hotel Application of humanoid robot near the reception desk for understanding the factors involved in robotic deployment	Peanut, humanoid telepresence robot	**Behavioral** Intent to use, human-robot interaction **Cognitive** Acceptance	According to the results of this interview-based qualitative study (n=89), deployment of service robots depends on the acceptance of robots by guests. Acceptance of robots by guests was contingent on robotic, organizational, and human related dimensions. In Thailand, different stakeholders (i.e., staff and guests) are tended to accept robots for hotels.	Sadangharn, 2022
	Various, humanoid and machine-like	**Behavioral** Customer engagement: Intention to revisit, Willingness to recommend **Cognitive** Service quality	According to the content analysis of online reviews from customers from Japan and the USA, results revealed that robotic services significantly improve the quality of service offered to travelers, while positively affecting travelers' intention to revisit robotic hotels within the context of customer engagement behaviors (CEBs).	Çakar & Aykol, 2021

	Hotel/Restaurant Online reviews of ro-bot- staffed hotels and restaurants in China		**Cognitive** Amazement, Socio-emo-tional elements, Rela-tional elements, Func-tional elements of the sRAM model	According to the text mining analysis of 7994 online reviews from Trip Advisor, the principal dimensions and variables involved in HRI and the feelings robots inspire in different types of travelers can be identified. The results showed that participants most often comment on the functional dimension of robots. Robots' functions determine this experience and influence the interaction between robots and hotel guests.	Fuentes-Moraleda et al., 2020
			Affective Customer positive and negative emotions	According to the text mining analysis of 7570 online reviews, functional and relational attributes of service robots are positively associated with customers' net emotions. However, physical attributes have contingent effects. For instance, consumers' higher attention to human-likeness of robots is negatively associated with net emotions.	Park et al., 2021
	Hotel/Restaurant Survey of consumers who interacted with service robots in tourism and hospitality contexts (e.g., waiters, hotel check in)		**Behavioral** Behavioral intention to use **Cognitive** Attitudes towards robots	In two survey studies with people (n=141; n=268) who interacted with service robots in hospitality settings, researchers found that the effect of perceived hedonic value on users' attitudes is contingent upon perceived utilitarian value. When utilitarian value is low, hedonic value negatively affects users' attitudes, leading service robots to be perceived as a gimmick. When utilitarian value is high, hedonic value positively contributes to users' attitudes, causing users to see service robots as a service improvement. Further, study 2 showed that perceived utilitarian and hedonic values evoke users' future behavioral intention. The strengths of these impacts depend upon users' previous experiences. Also, the effects of perceived values on behavioral intentions depend on the industry context (utilitarian vs. hedonic).	Hu, 2021
	Restaurant / Conference Introducing humanoid robots at a conference reception desk and restaurant (e.g., greeting, communication, food delivery)	Pepper, humanoid robot	**Behavioral** Adoption of humanoid robot	In this qualitative study with participants of a conference interacting with Pepper (n= 48), interview revealed emergent themes of suitability, agency, emotions, and technical factors related to the adoption of social robots in hospitality services.	Tuomi et al., 2021
Assistive Services	**Restaurant** Robotic services providing information, taking orders, preparing food, bringing dishes of	Various humanoid and machine-like robots	**Behavioral** Intention to use	Combing a survey with consumers (n=443) interacting with social robots in restaurants and interviews with hospitality managers in Singapore, this study reveals visitors' intentions to use social robots stem from the effects of technology acceptance variables (perceived usefulness, ease of use), service quality dimensions (service assurance, personal engagement, tangibles) leading to perceived value. Intention to use is also influence by social robots' empathy and information sharing behavior.	de Kervenoael et al., 2020

	food, and collecting trays or garbage				
	Restaurant/ Bar & Hotel Serving a guest in ordering and paying at a restaurant (Study 1). Serving a guest checking in (Study 2)	Pepper, humanoid; NAO, humanoid	**Cognitive** Trust	In two survey studies (n=202; n=406) with humanoid robots, this paper tests its proposed model of multifaceted trust in service robots comprised of three constructs - performance, process, and purpose - in a hospitality context. A higher-order formative construct of trust in service robots with the highest importance for a performance construct is identified (Study 1). Perceived risk and institution-based trust (structural assurance, situational normality) are identified as antecedents of the multifaceted trust in tourism service robots (Study 2).	Park, 2020
No clear explanation about the robot functionalities	**Restaurant/Bar** The role of consumer innovativeness	NA	**Affective** Desire **Behavioral** Intent to use and WOM	The results of this survey study (n=409) indicate that four underlying dimensions of consumer innovativeness (quality and hedonic experience seeking, venturesomeness and social distinctiveness) are indirectly related with desires and intentions. Other dimensions of consumer innovativeness (openness, vigilance, eagerness, and novelty seeking) are not related with these behavioral and cognitive outcomes.	Kim et al., 2020
	Various Service Industries Perceptions related to deployment of robots in tourism and hospitality	NA	**Affective** Overall experiential value	Results of the tourist interviews (n=8) indicate that tourist prefer anthropomorphic robots and use of anthropomorphic robots may increase the overall experiential value in tourism and hospitality.	Christou et al., 2020

Education *Antecedents / Service Settings*	*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Interaction with **NAO humanoid robot**	NAO, humanoid	**Cognitive** Acceptance	The results of a survey with preschool and elementary school teachers (n=17) demonstrated positive reactions toward and acceptance of the humanoid robot NAO.	Fridin & Belokopytov, 2014
			This cross-cultural student survey (n=158) shows that while Italian students were positive, English students were negative toward the perceived usefulness and intention to use the robot in psychological practice soon.	Conti et al., 2019
		Cognitive Learning, Pride, Interest	This case study demonstrated that the robot enhanced student's (n=53) pride and interest in Aboriginal language and culture. This project has confirmed for this school that using the robot as a teaching tool has enabled their students to connect in authentic ways with their local Aboriginal community by learning the Narungga language.	Keane et al., 2019
		Behavioral Challenges breakdowns	The results of the longitudinal field study with children (n=46) highlight four themes that offer explanations why children's interactions with the robotic tutor break down: (1) the robot's inability to evoke initial engagement and identify misunderstandings, (2) confusing scaffolding, (3) lack of consistency and fairness, and finally, (4) controller problems.	Serholt, 2018
		Cognitive Acceptance, Use cases, Challenges, Tensions	The results of in-depth interviews with teachers (n=3) who interaction with a NAO robot showed that teachers generally are responded positively to the idea of a future introduction of the robot in teaching, thereby envisioning differences in usage for teacher-robot and student-robot interactions. The research further highlights tensions with learning activities in the classroom leveraging Engeström's Activity System Model—a framework for analyzing human needs, tasks, and outcomes.	Ceha et al., 2022
Interaction with **ROBOVIE humanoid robot**	Robovie, humanoid	**Cognitive** Science curiosity	The results of the experiment with children (n=114) show that the interaction with Robovie did not affect the science curiosity of the entire class. However, the behavior of some children changed who became more curious to ask the robot additional science questions.	Shiomi et al., 2015
		Behavioral Interaction with robot	The results of this longitudinal field trial (n=37) reveal the children who treated Robovie as a peer-type friend established friendly relationships and continued interacting with it for the entire two months. Meanwhile, the children who did not consider Robovie as such a partner (two-thirds of the class) became bored with the robot after approximately five to seven weeks.	Kanda et al., 2007
Interaction with **RoboThespian humanoid robot** in two different classroom environments	RoboThespia, humanoid	**Cognitive**	The results of the experiment show that the elementary school children (n=189) successfully learned the subject (topic of "levers"). The learning	Verner et al., 2016

(1) studio (2) interactive laboratory		Learning	outcomes were evaluated by a quiz. The average score on the quiz was 68.3% for the students in the studio and 78.7% for those in the interaction laboratory. The level of learning interaction was influenced by the design of learning activities, robot behaviors, and the students' perceived psychological distance from the robot.	
Reading activity with a **learning-companion robot (Minnie)** vs. no robot	Minnie, humanoid/ cartoon-like	**Affective** Feelings of companionship and affiliation **Cognitive** Positive, Helpful, and engaging interaction, Learning, Motivation	The results of this field trial with children (n=24) suggest similar reading frequency and duration in both conditions (robot, no robot). Furthermore, children in both conditions described their experiences as positive, helpful for building reading skills and sustaining engagement. Children who read with the learning-companion robot further reported that the activities supported reading comprehension and motivated them to read and indicated a deepening social connection (i.e., companionship or affiliation) with the robot.	Michaelis & Mutlu, 2018
Interaction with **Tiro humanoid robot** in three classroom sessions	Tiro, humanoid	**Behavioral** Relationship establishing behavior, Open expressions of emotions	The analysis of questionnaires (n=33), interviews and video-ethnography show that in the early child-robot sessions, interactions were mostly related to the robot exterior and movement and other characteristics of the robot itself, while more interaction patterns related to its social attributes (e.g., giving of meaning, emotional expressions and relationship forming) were observed in later stages.	Oh & Kim, 2010
Use of **Pepper humanoid robot** for learning purposes in higher education	Pepper, humanoid	**Behavioral** Behavioral intention to rely **Cognitive** UTAUT	Survey results with university students (n=462) indicate that the four perceived characteristics of the robot (i.e., trustworthiness, adaptivity, social presence and appearance) all predict the intention to use Pepper for learning purposes, while anxiety and privacy were not significant predictors. Overall, the students do not have the intention to rely on social robots for learning purposes at the current level of state-of-the-art technology.	Guggemos et al., 2020
Use of Mero (humanoid) and Engkey (zoomorphic) robots for learning English as a second language	Mero, humanoid, Engkey, zoomorphic	**Cognitive** Learning, Satisfaction, Interest, Confidence, Motivation	Results of a field study in a Korean school (n=24) with two different learning assistant robots reveal that children's English-speaking skills significantly improved, however, listening skills did not. The interaction with the robot promoted and improved students' satisfaction, interest, confidence, and motivation in learning English.	Lee et al., 2011
Training in complex problem solving by a robot: **present vs. absent**	Myro, humanoid	**Behavioral** Task performance **Cognitive** Learning	The results of the experiment with children (n=37) show that children trained by Myro robot, not only showed significantly a greater progression in the number of Tower of Hanoi problems that they could solve accurately, but they also used considerably fewer steps than untrained children.	Resing et al., 2020
Students presenting **either assisted by a robot or PowerPoint**	Kebbi Air robot, humanoid/ zoomorphic	**Affective** Positive/negative emotions **Cognitive**	Results of the field experiment with middle school students (n=52) show that the students benefited from both presentation modes with enhanced digital storytelling outcomes. However, the robot-assisted mode was more advantageous than the use of PowerPoint in leading students to become grittier regarding learning tasks, to perform better in digital storytelling,	Hsieh & Lee, 2021; Hsieh, 2021 *(same study published in two outlets)*

		Digital storytelling outcomes grit perceptions	and to have more positive learning experiences—inclusive of positive emotions and positive perceptions.	
Employment of a **social robot** OR **gamification** OR both **robot and gamification in class**	Reeti Robot, cartoon-like	**Behavioral** Engagement **Cognitive** Motivation	Lab experiment with students (n=80) found no significant increase in engagement or motivation when adding gamification elements or the social robot. Combining both social robot and gamification resulted in lower student engagement.	Donnermann et al., 2021
Two lectures, **with and without robotic system** for asking questions, in counterbalanced order	CommU, humanoid	**Behavioral** Hesitation to ask questions, Activeness	Field experiment with university students (n=62) suggests that students who were usually hesitant to ask questions during lectures became less hesitant to ask questions face-to-face when they could use the proposed robotic system. Moreover, the perceived activeness in the lectures increased when using the system.	Shimaya et al., 2021

Elderly Care *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Interaction with an assisted living robot	Services for assistive living: shopping, garbage disposal, emergency alerts, reminding, physical walking support	Three Robot-Era robotic platforms (ORo, DoRo, CoRO), humanoid	**Cognitive** Preference for robotic services	The field experiments with older adults (n=45) show that elderly people with higher education levels evaluated robot's assisted living services (i.e., shopping, garbage disposal, indoor and outdoor walking support) higher than participants with a lower level of education. Males preferred shopping and indoor and outdoor walking support to females.	Cavallo et al., 2018
	Helping humans with household chores - shopping, reminders, garbage disposal, laundry, and food delivery		**Cognitive** Robot acceptance	The results of field experiments with elderly people (n=82) indicate that the multi-modal robots (offering a combination of assistive services) support more flexible and natural elderly–robot interaction, make clear the benefits for the users and, therefore, increase their acceptability.	Di Nuovo et al., 2018
Interaction with a socially assistive robot	Taking vital signs (e.g., blood pressure), reminding about medication, making telephone calls, playing music, and playing cognitive games	HealthBot Charlie, machine-like	**Behavioral** Robot use **Cognitive** Robot's mind perception, Attitudes towards the robot	The results of the field trial with older adults (n=23) indicate that those who held significantly more positive attitudes towards robots, and perceived robot minds to have less agency were more likely to use the robot. It was also found that attitudes towards robots improved over time in robot-users. These results suggest that the cognitions older people hold about robots may influence their decisions to use robots.	Stafford et al., 2014b
	Assisting older people in home setup (informing, playing music, measuring	NAO, humanoid	**Affective** Emotional, Engagement,	The results of the field trial with older adults (n=8) indicate that SARs were trusted by the participants. A cross–cultural comparison showed that results were not due to the cultural background of the participants. The	Torta et al., 2014

blood oxygen level, warning, video calls)		Perceived enjoyment **Cognitive** Trust	long-term evaluation showed that the participants might engage in an emotional relationship with the robot, but that perceived enjoyment might decrease over time.	
Messaging service, weather consulting, online grocery shopping, Internet, Skype, calendar with event reminder, medication reminder, robot navigation, and cognitive games	Kompaï, humanoid	**Affective** Enjoyment **Behavioral** Intention to use **Cognitive** Attitudes Perceived usefulness, Ease of use, Social influence, Barriers to acceptance	Elderly people (n=11) showed low intention to use the robot, as well as negative attitudes toward and negative images of this device. They did not perceive it as useful in their daily life. However, they found it easy to use, amusing, and not threatening. In addition, social influence was perceived as powerful on robot adoption. Direct experience with the robot did not change the way the participants rated robots in their acceptance questionnaire. Several barriers to robot-acceptance were identified, including older adults' uneasiness with technology, feeling of stigmatization, and ethical/societal issues associated with robot use.	Wu et al., 2014
Socially assistive services: medication reminders, agenda-keeping, nutritional advises, motivation for physical activity, safety monitoring etc.	GrowMu, humanoid	**Cognitive** Robot roles	Based on the in-depth, scenario-based interviews with older adults (n=20) the authors propose a typology that identifies six roles of socially assistive robots in an elderly person's value network (enabler, intruder, ally, replacement, extended self, and deactivator) and links them to three health-supporting functions by robots: safeguarding, social contact, and cognitive support.	Čaić et al., 2018
Speech-based computerized cognitive testing	PaPeRo R500, humanoid	**Cognitive** Reliability and acceptability of the robot test	This experimental study with seniors (n=66;40) suggests the possibility that cognitive tests using social robots as user interfaces can be reliable for and acceptable to community-dwelling older adults.	Takaeda et al., 2019
Socially assistive services: entertaining and stimulating older adults for physical activity	Zora (NAO hardware), humanoid	**Cognitive** Barriers to use, Value	Interviews, questionnaires, and observations with elderly people (n=44) and care professionals (n=18) were used to investigate the interactions with the Zora robot. Care professionals experienced several barriers in the use of the robot (e.g., start-up time and software failures). They mentioned that the robot had a positive influence on clients as it created added value for the care professionals in having fun at work.	Huisman & Kort, 2019
Instructing older adults in physical exercise, giving dance-shows, and playing different kinds of games		**Cognitive** Public opinion	The results of this case study (n=39) show that public opinion about SARs is mainly negative, but that the commentators apparently have little information about the robot and its tasks. The personnel had more positive views; they saw it as a recreational tool, not as a replacement for their own roles.	Tuisku et al., 2019
Rehabilitation and recreational assistance with exercise, playing music, per-		**Behavioral** Increase in exercising and interacting of clients	The results of focus groups and field trials with elderly people and care professionals (n=40) show that: - for elderly people: impact on interaction and activities. The robot's presence stimulated the clients into exercising and interacting.	Melkas et al., 2020

	forming dances, storytelling, and playing interactive memory and guessing games.		**Cognitive** Work atmosphere, Meaningfulness of work content, Professional development	- for care personnel: impacts on the work atmosphere, meaningfulness of work content, and professional development. Impacts on personnel were related to the need for orientation, problems of time usage, and overall attitudes toward novelty and renewing of care service.	
	Using various assistive technologies to assist in the home-care of older people	Various	**Behavioral** Willingness to use, First use and continuing use	The results of this cross-cultural survey study (n=1004) show that compared to Finland and Ireland, Japanese people were already familiar with robots in their daily lives and associate them with safety. In Finland, people had more negative impression of robots compared to the other two countries. Besides, Ireland and Finland emphasized the need to guarantee the entitlement to receive human care.	Suwa et al., 2020
	Walking with elderly, conversation during joint walk	Robovie, humanoid	**Behavioral** Laughing, Smiling, Steps taken, Walking style **Cognitive** Subjective enjoyment, Anxiety	The results of the field experiment (n=23) revealed that the participants experienced more enjoyment from walking with the robot than from walking alone. Moreover, the results of the time and steps analysis revealed no differences in physical burden between walking styles in the experiment, although the effect size suggested the possibility of an influence based on the time. The comments from some participants suggested that walking with the robot evoked a perception of novelty or stimulated an existing interest in assistive robotics, resulting in positive effects.	Nomura et al., 2021
	Assisting elderly in daily living e.g., by reminding them to take medicine, carry things, support elderly in taking a bath, or playing games together	Buddy, Cartoon-like	**Cognitive** Acceptance, Task type, Usability, Ease of use, Attitudes	The results of two qualitative studies (n=36 and n=29) conducting in-depth interview before and after a video presentation of an assistive robot revealed that there were significant differences in the attitudes, usability, and ease of use of elderly people towards robot assistance before and after watching the Buddy Robot video as such that they had a more positive attitude after watching the video. The elderly was more receptive to the use of robots in more neural activities (e.g., reminding of medicine) compared to the use of robots in group or private activities (e.g., playing mahjong, taking a bath)	Huang & Huang, 2021
Comparison study: i) assisted living services, ii) socially assistive services and iii) socially interactive services	cooking demonstration (PR2), work assistant (NAO), companionship (Paro), socially assistive tasks (ElliQ), smart house (Google home), playing physical game (Cozmo)	PR2, NAO, humanoid; Paro, zoomorphic; ElliQ, Google Home, Cozmo, machine-like	**Affective/ Cognitive** User needs and concerns	Video-based interviews with older adults (n=30) and the analysis of their reaction to videos of six different types of robots uncover four user needs that can be threatened by the introduction of home robots: the need for independence, the need for control, the fear of being replaced, and the need for authenticity.	Deutsch et al., 2019

Healthcare *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Verbal Medical Assistance Interview with patients; Medical Recording Interacting with children, playing games, giving medical instructions	Deploying robot for collecting medical data	Pepper, humanoid	**Behavioral** Task duration taking medical *Robot Performance to detect patient characteristics	In a randomized control trial (n=42), social robot *Pepper* autonomously, effectively, and acceptably assists healthcare professionals by interviewing older adults and collecting self-reported medical data.	Boumans et al., 2019
	Patient Characteristics (Emotional Coping Strategy)	Alice R50, humanoid	**Behavioral** Distance, Use intentions **Cognitive** Robot appraisal affordances, Ethics, Aesthetics, Realism, Relevance,	Participants' (n=141) perception of humanoid robot (*Alice*) is indirectly affected by their emotional state and coping potential through appraisal of coping potential. Robot perceptions (e.g., affordances, ethics) were affected by positive emotion-focused coping strategy.	Spekman et al., 2018
	Deploying robot in child care units	NAO (Medi), humanoid	**Cognitive** Themes, Ideas how to integrate MEDI in daily work at hospital, How would it impact the hospital	In this case study which included participants (n=7) who interacted with the robot over a longer period in a childcare unit several challenges and successes related to the adoption process where revealed. Moreover, the professionals explained how using the robot aligned with their roles and responsibilities of their profession. The interviews further revealed the friendly emotional impact the robot had on the hospital environment.	Beran et al., 2021
Verbal Medical Care Therapy	Scenario of applying socially assistive robots in therapy	Pepper, humanoid	**Cognitive** Robot acceptance	Results from 6 focus groups (n=19) show that therapists are more acceptant about socially assistive robots in therapy after the presentation of the robot. Addressing participants' knowledge and understanding of the proposed robot and its purpose in therapy has an immediate, positive impact on therapist acceptance. Further, the results indicate that demographics and societal factors are linked to patient engagement with robots. Patients who pay for private therapy are somewhat more motivated to engage with the robot. Also, the robot acceptance of those close to the patient (e.g., spouse, parents/children, friends) influences engagement.	Winkle et al., 2020
	Using robots in psychotherapeutic treatment	NAO, humanoid	**Behavioral** Decrease in calorie intake	Content analysis of 26 trial participants' interviews shows that a social robot is effective at psychotherapeutic treatments. Health behaviors of the participants have changed, and calorie intake has reduced. Robots are perceived as interactive and sociable actors.	Robinson & Kavanagh, 2021
Verbal + Physical Medical Coaching/Care	Using robot in rehabilitation session	NAO, humanoid	**Behavioral** Engagement, Independence **Cognitive**	In a qualitative study and a field trial, humanoid social robots (*NAO*) were perceived as complementary actors in rehabilitation therapies and to have therapeutic value from parent and child perspectives (n= 6 families). The robots promote child engagement and independence during exercises.	Butchart et al., 2019

Instructions for Physiotherapy; Measurements, warming, the physical exercise, the cooldown, final measurement; Rehabilitation therapy; Cardiac training with vs. without social robot interaction/motivation			Perceived value		
			Cognitive Usefulness, Trust, Safety, Utility	Most of the patients (n=28) and clinicians (n=15) have positive perceptions (usefulness, utility, safety, and trust) of using humanoid, social robots (*NAO*) in cardiac rehabilitations. Positive perception of users increases after interaction with the robot.	Casas et al., 2019
			Behavioral Gaze & communication behavior **Cognitive** Positive and negative emotions, Attitude towards the robot	In a field experiment (n=177), engagement, motivation, and positive emotions (enjoyment) of 177 school children and three child patients increased while conducting upper-limb rehabilitation tasks and playing with humanoid, social robot *NAO*. Children described the robot mostly as *happy*, *clever*, and *loving* and least as *absent*, *silly*, and *angry*. Without any help, children intuitively learned how to train with the robot by themselves.	Pulido et al., 2017
			Affective Resting heart rate, Recovery heart rate **Behavioral** Response time to robot, Posture correction, Nonattendance rate **Cognitive** Robot perception	This longitudinal study (n=6 and 209 rehab sessions) found that patients felt more encouraged to perform physical activity and continue with the rehabilitation when they perceived that are being monitored and supervised by the system. Further, the intervention group experienced a positive impact while working with the robot, increasing their confidence and willingness to continue the therapies. Moreover, the system presented a reliable performance at monitoring possible risk factors associated to the therapy. This was supported by the patients' perception as they felt that the system provided safety to the therapy and controlled their parameters to avoid health risks.	Casas et al., 2020
		Baxter, machine-like	**Behavioral** Number of tries, Task clarifications **Cognitive** Attitude toward technology, Effort expectancy t1: Forms of grouping, Performance expectancy, Reciprocity, Self-efficacy, Attachment t2: Pleasure, Energy, Enjoyability, Engagement level, Exercise level, Pain level, Safety level	In a lab experiment (n=40), researchers found that only socially and physically interactive games fell in the highest ranges for pleasantness, enjoyment, engagement, cognitive challenge, and energy level. Thereby the researchers' developed games successfully spanned three different physical, cognitive, and temporal challenge levels. User trust and confidence in Baxter increased significantly between pre- and post-study assessments. Furthermore, older adults experienced higher exercise, energy, and engagement levels than younger adults, and women rated the robot more highly than men on several dimensions.	Fitter et al., 2020
Verbal + Physical Medical Assistance	Scenario of working with	Various care robots	**Cognitive**	Using the mixed method approach of Q-methodology, researchers find potential users (n=116) have concerns related to increasing dependency on technology providers. Some of the potential users think that robots reduce	Mettler et al., 2017

Room service, Medication, Care support, Cleaning, Transportation	robots in hospitals and care facilities		Perceptions & attitudes related to service robots in hospitals	workload of professionals and perceive social robots as strategic assets. Results reveal that potential users believe that social robots will only help and not substitute skilled professionals and that social robots improve health service quality.	

Public Services *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Public Services	Robots in Museums	Pepper, humanoid	**Cognitive** Acceptance of social robots in museums, Visitor experience, empathy, Personal engagement	In this scenario-based study (n=433) a multidimensional instrument for measuring willingness to accept social robots in museum contexts is developed. Willingness is determined by three factors: museum visitor experience, empathy, and personal engagement; younger individuals (under 30 years old) showed a higher degree of acceptance of social robots than do visitors over 30.	Fuentes-Moraleda et al., 2022
Security	Robot application in Security/Peacekeeping	Robocop, humanoid	**Cognitive** Trust, Reliance intentions, Desire to use in different settings	Females reported higher trust and perceived trustworthiness of the autonomous security robot *Robocop* preventing unauthorized personnel from gaining access to a secure area relative to males in a video-based experiment with US-American adults (n=200). Further, females' (versus males') perceptions of the robot's ability and its benevolence toward others was greater and they expressed greater desire to use the robot in hospitals and on college campuses; no gender differences were found for perceptions of integrity and military versus public use of the robot.	Gallimore et al., 2019
	Security/Entry control at public social event	Baxter, humanoid	**Cognitive** Human-likeness, Intelligence, Perfect automation schema, Affect	In a video-based study in the context of robotic entry control at a public event (n=233), human-related (i.e., perfect automation schema, positive and negative affect) and robot-related metrics (i.e., human-likeness, intelligence) were found to affect trust in the security robot mediated by trustworthiness measure's ability and integrity.	Kim et al., 2020

Retail *Antecedents / Service Setting*		*Robot Type*	*Consumer Outcomes*	*Key Findings*	*Authors*
Retail Shopping Mall & Stores	Robot application in a shopping mall Assisting and Guiding, Quizzing, Recommending, Entertaining	Robovie, humanoid	**Behavioral** User Engagement (Interacting with robot)	In a field study with customers in a shopping mall (n=67) in Japan interaction with humanoid robot *Robovie*, subsequent qualitative interviews revealed that families with children tend to view the robot more favorably because their children openly expressed interest in it by running toward it and talking with it. Visitors engaged differently with the robot due to a complex mix of the following indicators: the mental associations between the robot and its location (nature of public places), its assigned future roles and the perception of its autonomy.	Sabelli & Kanda, 2016
		Human-sized, humanoid robot	**Affective** Emotions (Enjoy, Curiosity, Stress, Pain) **Behavioral** Abusive behavior towards robot **Cognitive** Perceived robot capability to understand abusive behavior	In a field study in a shopping mall in Japan, qualitative interviews with children (n=28) who abused a human-sized, humanoid robot revealed that children explain their abusive behavior with curiosity, enjoyment, or triggered by others; and not with an intention to hurt the robot. Most of the children perceive the robot not as just a machine, but a human-like entity and half of them believed the robot had the capability to perceive their abuse, yet they engaged in it.	Nomura et al., 2016
		Pepper, humanoid	**Behavioral** Number of started interactions, Number of people attracted, Number of people entering the store, Number and time of transactions	By conducting an observation (n=1336 observation before chocolate store) study in the field, researchers found that the better placement of humanoid social robots (inside or outside the store) is contingent on the goals the retailer prioritizes. To create awareness and interest towards the store, the HSR should be placed outside, as it has double the stopping power; to induce consumers to enter the store, placement of the HSR inside the store is the better option. In general, outside placement of the robot is more effective related to the number of transactions and total amount spent.	De Gauquier et al., 2021
			Cognitive Sharing of personal information	Results of a video-based survey (n=464) revealed that service quality, enjoyment, and usefulness, which are determined by self-interest, and trust, which is determined by social interaction, predicted consumers' willingness to share information with a fashion sales robot. Particularly, service quality and enjoyment were the most influential factors in consumers' willingness to share their personal information in this retail setting.	Song & Kim, 2021
			Cognitive Themes that capture customer acceptance of robots in retail banking	In a mixed method study (observations (n=26), focus groups (n=26), interviews (n=15)) 16 dimensions that group into five main themes that influence customer acceptance of service robots in retail banking services: (1) utilitarian aspect, (2) social interaction, (3) customer responses toward	Amelia et al., 2022

				robots, (4) customer perspectives of the company brand and (5) individual and task heterogeneity are identified. While themes 1 and 2 confirmed themes based on existing theoretical frameworks used; themes 3–5 are newly identified themes	

Arts & Entertainment *Antecedents / Service Setting*		*Robot Type*	*Outcomes*	*Key Findings*	*Authors*
Socially Interactive Services	**Exhibition** Interaction with Robots placed in Art Exhibition (machine-like that interacts through Touch; human-like that interacts verbally)	The Blind Robot, machine-like; Geminoid-DK, android	**Cognitive** Robot experiences, Preferences to touch the robots	In a field trial, two robots with different morphologies were placed in an arts exhibition and participants were allowed to interact with them as they pleased. The machine-like (The Blind Robot) was more preferred by users (n=50) than the android robot (Geminoid-DK) and visitors found its movements more appealing. Visitors also felt more connected with the machine-like robot because it met their expectations better as android robots might set expectations too high. Post interactions, visitors preferred to touch the machine-like "hard" robot despite initial stated preference for soft materials. They further preferred mutual contact despite initial preference of subject to initiate touch, and preferred communication with a robot that could touch (vs. „see ").	Vlachos et al., 2016

Appendix F: Full List of Included Articles in Literature Review (Chapter 3)

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Appendix G: Full List of Articles Considered based on Literature Review (Chapter 5)

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Appendix H: Sample Overview of Qualitative Study (Chapter 5)

ID	Role in Organization	Sex	Hierarchy level	Duration of interview [min]	Tenure [years]	Institution	Format
FKB1	Customer Advisor	m	Employee	67	7	Cooperative bank	Tel
FKB2	Customer Advisor	m	Employee	113	10	Cooperative bank	Tel
FKB3	Customer Advisor	m	Employee	55	20	Private bank	Tel
FKB4	Customer Advisor	m	Employee	59	n.s.	Cooperative bank	F2F
FKB5	Customer Advisor	m	General manager, head of customer advisory	56	n.s.	Cooperative bank	F2F
FKB6	Customer Advisor	f	General manager, branch manager in customer advisory	48	n.s.	Cooperative bank	Tel
FKB7	Customer Advisor	m	Employee	40	2,5	Cooperative bank	Tel
PKB1	Private Advisor	m	Employee	37	3,5	Cooperative bank	Tel
PKB2	Private Advisor	m	Employee	48	8	Cooperative bank	Video call
PKB3	Private Advisor	m	Self-employed financial advisor	45	6	Financial advisory	Tel
PKB4	Private Advisor	m	Branch director	47	10	Cooperative bank	Tel
A1	Analyst	m	Employee	59	20	Cooperative bank	Tel
A2	Analyst	m	Employee	52	n.s.	Cooperative bank	F2F
A3	Analyst	m	Branch manager in Central Credit Service	53	n.s.	Cooperative bank	Tel
			Average	55.6	9.7		
			Median	52.5	8.0		

Note. n.s. = not stated; Tel = Telephone; F2F = face to face.

Appendix I: Interview Guide (Analysts; Chapter 5)

- *Brief **introduction** of interviewer and study objective.*
- *Asking for **permission to record and transcribe** the interview; anonymized, so that no conclusions about your person are possible or intended.*
- *Information on **appr. length of interview**.*
- *Ask for **open questions** before the interview.*
- *Start the audio recording. [Obvious **placement** of the recording device]*
- ***Verification of recording agreement**. "Can you please briefly confirm that you have given your consent for our conversation to be recorded."*

Introduction:
Artificial intelligence (AI) Artificial intelligence (AI) offers great potential and opportunities, especially for financial service providers. Today, AI is already used in many ways in banks, for example in fraud detection, customer advice and business model development. There is further potential, which is expected to have a major impact on the competitiveness and growth of financial institutions. AI as self-learning technology is often used in service companies as internal support software for the employee. The AI, that interacts with the employee in a human-like manner, can be seen as an internal service provider to the em-ployee. AI systems therefore mean more than just automating processes. They complement human abilities and thus achieve better outcomes together than they could on their own. Employees in particular play an important role here, as they can be strongly supported by AI in their daily work.

Objective of the interview:
The aim of the interview is to answer these questions from the perspective of relevant bank employees: How can such service tasks be effectively performed by such human-AI teams? **How can such a collaboration between employee and AI be ideally designed and what characteristics would the AI need to have?**
Thereby, the ideas of the employees, who are already working with the AI or who could theoretically work together in the future, are relevant. In the field of financial services, relevant areas of application for such collaboration are **customer advisory service and credit analysis/risk analysis**.

Note: For reasons of better understanding, the simultaneous use of masculine and feminine forms of language is foregone. All references to persons apply equally to both genders.

Moderation instruction: All questions with a grey background must be asked. All other questions serve as support and are asked if the interviewee does not make a statement beforehand.
[60 minutes / 24 questions]

1 Warm-up questions *[4 min / 5 questions]*

1.1 How long have you been working as an analyst?

1.2 Briefly describe your job in a few sentences.
How does an analysis proceed?

1.3 What do you understand by artificial intelligence (AI)?
Definition of AI by interviewee

1.4 Do you use AI in your company?
Is this planned?
If yes, what does the application of AI look like? What should the application of AI look like? Are you working with an AI or is this planned?

1.5 Can you imagine working with an AI?
If no, why?

2 Imagination & expectation regarding cooperation with an AI *[3 min / 1 question]*

2.1 How do you imagine a collaboration between you as an analyst and an AI?
If applicable, specify on AI-based system

- How do you envision the **division of tasks** between you as an analyst and the AI-based system?
- What do you **expect** from the cooperation with an AI-based system?
- What can this look like in conrete terms?

3 Characteristics of AI – identification *[8 min / 2 questions]*

If cooperation with an AI cannot be imagined, the scenario is already explained here. This will be taken into account in the evaluation.

3.1. Describe how an optimal collaboration between you and an AI-based system is designed.

- What does **optimal** mean to you in this context?
- What is **important** in the cooperation?
- What features does an AI-based system need to have in order for you to be able to optimally work with it / to make good collaborative decision? Why?
- How do these characteristics **manifest itself** in the cooperation?
- What features of the AI-based system do you feel are **important** for optimal collaboration?
- Where appropriate, what is your **role** in the collaboration? What is the role of the AI?
- Where appropriate, what does the AI **do**?

3.2. Do you see problems/ obstacles in the cooperation between you as an analyst and an AI-based system? Describe which ones.

- What should be **considered/ avoided**?
- What **features** must an AI-based system not have for optimal collaboration? Why?
- How do these features **manifest itself** in the collaboration?
- Where appropriate, What is the AI not allowed to do?

4 Feature validation

Transparency – understanding, importance/need, manipulation check
[10 min / 5 questions]

4.1 What do you understand by transparency in the cooperation with an AI-based system?

- What **does it take** for you to perceive collaboration with an AI-based tool as transparent?
- How does this **manifest itself** in the cooperation?
- What do you understand by transparency of **decisions**?

- What do you understand by transparency of **actions**?

4.2 How do you <u>evaluate</u> the transparency of decisions/actions in the cooperation with an AI-based system?

- How **important** is transparency of decisions/actions to you when working with an AI-based system?

Please put yourself in the following situation:

You are conducting a risk analysis for a real estate loan. This is intended for a long-standing business client who wants to expand his production facilities with the help of the loan. For the analysis, you use a system that makes all client's financial information accessible and thus provides an all-round view of the client. Recently, this has been running on AI-based software. This carries out complex data analyses for you and makes a risk assessment and recommendation.
Reference value when asked: €1 million

- Is that understandable for you? Can this happen in your job?
- What is it like working with consultants**?**

4.3 Imagine that you were aware of the parameters according to which the AI-based system acts and decides: To what extent would you consider this transparent?

- How do you feel about this?

4.4 Imagine that the system explained the results of the analysis to you: To what extent would you perceive this as transparent?

- How do you feel about this?

4.5 Would anything else be needed for you to perceive the cooperation to be transparent? What?

Reciprocal Strength Enhancement– understanding, importance/need, manipulation check
[8 min / 4 questions]

4.6 What do you <u>understand</u> by the fact that you as an analyst and the AI-based system strengthen each other's strengths when collaborating?

- Where do you see **human strengths** in your work?
- How can AI **increase/improve/strengthen these strengths** through collaboration?
- Where do you see the **strengths of the AI**?
- How can the employee **increase/improve/strengthen these strengths of the AI** through a collaboration?
- How does this **manifest itself** in the cooperation?

4.7 How do you <u>evaluate</u> the mutual strengthening of strengths in the collaboration with an AI-based tool?

- How **important** is it for you to strengthen each other's strengths when working with an AI-based tool?

Please put yourself back in the situation described.

Imagine that the AI-based tool supports you in a task *(e.g., in a complex data analysis, so that you can focus on the interpretation of the data)***. At the same time, you give the AI-based tool feedback** *(e.g., on its analyses as well as the results and effects of its decisions)***, which helps it to learn. You have the feeling that the decisions of the AI and thus your personal analysis results are continuously being improved.**

4.8 To what extent would you find this as mutually strengthening strengths?

- How do you feel about this?

4.9 Would you need anything beyond that to feel that the collaboration is mutually strengthening strengths? What?

Engaging – understanding, importance/need, manipulation check
[8 min / 4 questions]

4.10 What do you understand by the AI-based system actively interacting with you in the collaboration?

- What **does it take** for you to perceive the AI-based tool as actively interacting in the collaboration?
- How does this **manifest itself** in the cooperation?

4.11 How would you evaluate that the AI-based system actively interacts with you in the collaboration?

- How i**mportant** is it to you that the AI-based system actively interacts with you in the collaboration?

Please put yourself back in the situation described.

You give feedback to the AI-based system as described. You can give the system feedback via a chatbot module. Every now and then, the AI asks you more precisely what you mean by your feedback. You can also ask the system specific questions about individual analyses.
The system asks you via the chatbot module whether you agree with the risk assessment or whether you would make adjustments based on your personal assessment of the risk potential.

4.12 To what extent would you perceive the AI-based system as actively interacting in the collaboration?

- How do you feel about this?

4.13 Would it take anything beyond that for you to perceive the AI-based system as actively interacting in the collaboration? What?

Process Control – understanding, importance/need, manipulation check
[8 min / 4 questions]

4.14 What do you understand by having control in the process of working with the AI-based system? (possibly in the product selection?)

- What **does it take** for you to feel process control when working with the AI-based system?
- How does this **manifest itself** in the cooperation?

4.15 How do you evaluate having control in the process when working with an AI-based system?

- How **important** is process control to you when working with an AI-based system?

Please put yourself back in the situation described.

You have the possibility to adjust the limits of decision parameters, such as the economic equity, the operating result or the debt capacity.

4.16 To what extent would you feel process control when working with the AI-based system?

- How do you feel about this?

4.17 Would it take anything beyond that for you to perceive process control in the collaboration with the AI-based system? What?

Ouctome Control - understanding, importance/need, manipulation check *[8 min / 4 questions]*
4.18 What do you <u>understand</u> by having control over the outcome when working with an AI-based system? • What **does it take** for you to feel process control when working with the AI-based system? • How does this **manifest itself** in the cooperation? **4.19 How do you <u>evaluate</u> having this control over results when working with an AI-based system?** • How **important** is control over results to you when working with an AI-based system? **Please put yourself back in the situation described.** **If necessary, you are able to adjust the artificial intelligence's final decision on lending.** **4.20 To what extent would you perceive control over results when working with the AI-based system?** • How do you feel about this? **4.21 Would it take anything beyond that for you to perceive control over results when working with the AI-based system? What?**
5 Final questions
5.1 Which of the aspects we have covered are particularly important to you when working with an AI-based system? **5.2 Is there anything else you would like to add that is important to you in this context but has not yet been covered?** • Are there any questions you thought I would ask but which did not come up in the interview?

Appendix J: Interview Guide (Customer Advisor; Chapter 5)

- *Brief **introduction** of interviewer and study objective.*
- *Asking for **permission to record and transcribe** the interview; anonymized, so that no conclusions about your person are possible or intended.*
- *Information on **appr. length of interview**.*
- *Ask for **open questions** before the interview.*
- *Start the audio recording. [Obvious **placement** of the recording device]*
- ***Verification of recording agreement**. "Can you please briefly confirm that you have given your consent for our conversation to be recorded."*

Introduction:

Artificial intelligence (AI) Artificial intelligence (AI) offers great potential and opportunities, especially for financial service providers. Today, AI is already used in many ways in banks, for example in fraud detection, customer advice and business model development. There is further potential, which is expected to have a major impact on the competitiveness and growth of financial institutions. AI as self-learning technology is often used in service companies as internal support software for the employee. The AI, that interacts with the employee in a human-like manner, can be seen as an internal service provider to the employee. AI systems therefore mean more than just automating processes. They complement human abilities and thus achieve better outcomes together than they could on their own. Employees in particular play an important role here, as they can be strongly supported by AI in their daily work.

Objective of the interview:

The aim of the interview is to answer these questions from the perspective of relevant bank employees: How can such service tasks be effectively performed by such human-AI teams? **How can such a collaboration between employee and AI be ideally designed and what characteristics would the AI need to have?**

Thereby, the ideas of the employees, who are already working with the AI or who could theoretically work together in the future, are relevant. In the field of financial services, relevant areas of application for such collaboration are **customer advisory service and credit analysis/risk analysis**.

Note: For reasons of better understanding, the simultaneous use of masculine and feminine forms of language is foregone. All references to persons apply equally to both genders.

Moderation instruction: All questions with a grey background must be asked. All other questions serve as support and are asked if the interviewee does not make a statement beforehand. [60 minutes / 24 questions]

1 Warm-up questions *[4 min / 5 questions]*

1.1 How long have you been working as a customer advisor?

1.2 Briefly describe your job in a few sentences.
Advisor/consultant: How can I imagine your advisory services?

1.3 What do you understand by artificial intelligence (AI)?
Definition of AI by interviewee

1.4 Do you use AI in your company?
Is this planned?
If yes, what does the application of AI look like? What should the application of AI look like? Are you working with an AI or is this planned?

1.5 Can you imagine working with an AI?
If no, why?

2 Imagination & expectation regarding cooperation with an AI *[3 min / 1 question]*

2.1 How do you imagine a collaboration between you as an analyst and an AI?

If applicable, specify on AI-based system

- How do you envision the **division of tasks** between you as an analyst and the AI-based system?
- What do you **expect** from the cooperation with an AI-based system?
- What can this look like in conrete terms?

3 Characteristics of AI – identification *[8 min / 2 questions]*

If cooperation with an AI cannot be imagined, the scenario is already explained here. This will be taken into account in the evaluation.

3.1 Describe how an optimal collaboration between you and an AI-based system is designed.

- What does **optimal** mean to you in this context?
- What is **important** in the cooperation?
- What features does an AI-based system need to have in order for you to be able to optimally work with it / to make good collaborative decision? Why?
- How do these characteristics **manifest itself** in the cooperation?
- What features of the AI-based system do you feel are **important** for optimal collaboration?

In case of little comprehension:

- Where appropriate, what is your **role** in the collaboration? What is the role of the AI?
- Where appropriate, what does the AI **do**?

3.2 Do you see problems/ obstacles in the cooperation between you as a customer advisor and an AI-based system? Describe which ones.

- What should be **considered/ avoided**?
- What **features** must an AI-based system not have for optimal collaboration? Why?
- How do these features **manifest itself** in the collaboration?
- Where appropriate, What is the AI not allowed to do?

4 Feature validation

Transparency – understanding, importance/need, manipulation check
[10 min / 5 questions]

4.1 What do you <u>understand</u> by transparency in the cooperation with an AI-based system?

- What **does it take** for you to perceive collaboration with an AI-based tool as transparent?
- How does this **manifest itself** in the cooperation?
- What do you understand by transparency of **decisions**?
- What do you understand by transparency of **actions**?

4.2 How do you <u>evaluate</u> the transparency of decisions/actions in the cooperation with an AI-based system?

- How **important** is transparency of decisions/actions to you when working with an AI-based system?

Please put yourself in the following situation:

A long-standing business client of yours would like to take out a real estate loan in order to expand his production facilities. To suggest suitable products to the customer, you open the banking system and call up the customer's profile in the system. Recently, the banking system has been running on AI-based software. This software carries out complex data analyses for you and generates an individual product recommendation.
Reference value on demand: € 1 million

- **Can you put yourself in this position?**
- **Can this be applied in your job?**

4.3 Imagine that you were aware of the parameters according to which the AI-based system acts and decides: To what extent would you consider this transparent?
4.4 Imagine that the system explained the results of the analysis to you: To what extent would you perceive this as transparent?

4.5 Would anything else be needed for you to perceive the cooperation to be transparent? What?

Reciprocal Strength Enhancement– understanding, importance/need, manipulation check
[8 min / 4 questions]

4.6 What do you understand by the fact that you as a customer advisor and the AI-based system strengthen each other's strengths when collaborating?

- Where do you see **human strengths** in your work?
- How can AI **increase/improve/strengthen these strengths** through collaboration?
- Where do you see the **strengths of the AI**?
- How can the employee **increase/improve/strengthen these strengths of the AI** through a collaboration?
- How does this **manifest itself** in the cooperation?

4.7 How do you <u>evaluate</u> the mutual strengthening of strengths in the collaboration with an AI-based tool?

- How **important** is it for you to strengthen each other's strengths when working with an AI-based tool?

Please put yourself back in the situation described.

Imagine that the AI-based tool supports you in a task *(e.g., in the product selection for customers, so that you can save time and focus on the personal conversation with the customer)*. **At the same time, you give the AI-based tool feedback (***e.g., on its product selection as well as the results and effects of its decisions)***, which helps it to learn. You have the feeling that the selection of the AI and thus your personal advisory results are continuously being improved.**

4.8 To what extent would you find this as mutually strengthening strengths?

4.9 Would you need anything beyond that to feel that the collaboration is mutually strengthening strengths? What?

Engaging – understanding, importance/need, manipulation check
[8 min / 4 questions]

4.10 What do you <u>understand</u> by the AI-based system actively interacting with you in the collaboration?

- What **does it take** for you to perceive the AI-based tool as actively interacting in the collaboration?
- How does this **manifest itself** in the cooperation?

4.11 How would you <u>evaluate</u> that the AI-based system actively interacts with you in the collaboration?

- How i**mportant** is it to you that the AI-based system actively interacts with you in the collaboration?

Please put yourself back in the situation described.

You give feedback to the AI-based system as described. You can give the system feedback via a chatbot module. Every now and then, the AI asks you more precisely what you mean by your feedback. You can also ask the system specific questions about individual analyses.
The system asks you via the chatbot module whether you agree with the risk assessment or whether you would make adjustments based on your personal assessment of the risk potential.

4.12 To what extent would you perceive the AI-based system as actively interacting in the collaboration?
4.13 Would it take anything beyond that for you to perceive the AI-based system as actively interacting in the collaboration? What?

Process Control – understanding, importance/need, manipulation check
[8 min / 4 questions]

4.14 What do you understand by having control in the process of working with the AI-based system? (possibly in the product selection?)

- What **does it take** for you to feel process control when working with the AI-based system?
- How does this **manifest itself** in the cooperation?

4.15 How do you evaluate having control in the process when working with an AI-based system?

- How **important** is process control to you when working with an AI-based system?

Please put yourself back in the situation described.
You have the possibility to adjust the limits of decision parameters.

4.12 To what extent would you feel process control when working with the AI-based system?
4.13 Would it take anything beyond that for you to perceive process control in the collaboration with the AI-based system? What?

Outcome Control - understanding, importance/need, manipulation check
[8 min / 4 questions]

4.16 What do you understand by having control over the outcome when working with an AI-based system?

- What **does it take** for you to feel process control when working with the AI-based system?
- How does this **manifest itself** in the cooperation?

4.17 How do you evaluate having this control over results when working with an AI-based system?

- How important is control over results to you when working with an AI-based system?

Please put yourself back in the situation described.
If necessary, you are able to adjust the artificial intelligence's final decision on the product selection.

4.18 To what extent would you perceive control over results when working with the AI-based system?
4.19 Would it take anything beyond that for you to perceive control over results when working with the AI-based system? If so, what?

5 Final questions

5.1 Which of the aspects we have covered are particularly important to you when working with an AI-based system?
5.2 Is there anything else you would like to add that is important to you in this context but has not yet been covered?

Appendix K: Transcription Rules (Chapter 5)

1. It is transcribed literally, thus, not phonetically or summarizing. Existing dialects are not transcribed, but translated into standard speech as accurately as possible.
2. Language and punctuation are slightly smoothed, i.e., approximated to written speech. For example, “He’d named another book like that” is changed to “He had named another book like that”. Form of proposition, definite and indefinite articles etc. are maintained even if they contain errors. Repetitions that do not support or illustrate the content are omitted, whereas cases such as “very, very good” are transcribed.
3. Significantly longer pauses are marked by bracketed ellipses. According to the length of the pause in seconds, one, two or three ellipses are set. For longer pauses, the number corresponding to the duration in seconds is set.
4. Particularly stressed terms are indicated by underlines.
5. Very loud speaking is indicated by capital letters.
6. Approving sounds of the interviewer (mhm, aha, etc.) are not transcribed as long as they do not interrupt the interviewee’s speech flow.
7. Clauses lacking completion are marked with the sign “/".
8. Insertions of the respective other person are placed in brackets. E.g., [FKB1: Yes, important point.]
9. Sounds made by the interviewee that support or clarify the statements (e.g., laughter or sighs) are noted in brackets. E.g., (FKB1: assent hmh).
10. Paragraphs of the interviewer are marked with an “I:” that of the interviewee as follows:
    Corporate client advisor-> FKB1, FKB2, …
    Privat client advisor -> PKB1, PKB2, …
    Analyst -> A1, A2, ….
11. Each speaker’s contribution is transcribed as a separate paragraph. Speaker change is made clear by pressing the Enter key twice, i.e., blank line between the speakers, in order to increase readability.
12. Disturbances are noted in brackets with the cause, e.g., (cellphone rings)
13. Incomprehensible words are identified by (unv.).
14. All information that allows conclusions to be drawn about an interviewee, a company, partners or competitors, is anonymized.
    Employer names -> “employer“
    Partner names -> “partner“
    Competitor names -> “competitor“

Note. cf. Kuckartz, U. (2014). Qualitative Inhaltsanalyse. *Methoden, Praxis, Computerunterstützung* (2. Auflage). Weinheim und Basel: Beltz Juventa.

Appendix L: Example Quotes per CI System Feature (Chapter 5)

CI system Feature	Example Quotes (Translated in English)
Reciprocal Strength Enhancement	"(…) *on the one hand the system naturally learns from me. So, learn from the criteria, from the decisions by also defining the decision/criteria somewhere. And on the other hand, of course, the system, now imparts knowledge to me (the consultant). In other words, knowledge that would not have been possible now, due to network analysis, due to the merging of certain data, i.e., customer data*." (FKB 1)
Engagement	"*In principle, if the AI (...) points out mistakes or omissions, that's of course also very important*."(A1) "*That I already get the appropriate feedback during the preparation, or during the data collection or during / So in this process, so to speak. Or because decision-making aids are already installed. […] When you end up typing in something that he says to you, "Oh. That's just not plausible. The one piece of information you just gave me doesn't match up 100 percent with this piece of information. I either need more information or check again*." (FKB4)
Transparency	"*Yes, definitely insight at any time; (...) that it is explained exactly how the artificial intelligence worked. (...) that is explained precisely [...] why did it make the decision like that.*“(PBK1) “*In principle, the result of this risk analysis should be easy to understand. So not only that it spits out the red, green, yellow systemization, but also with a reason why*.” (A1) "*Which criteria have now led to this decision or perhaps to another decision, or done the task in this way or in this way? So, I still have to be able to see certain things. So at least certain criteria: Why has this system now decided on the amount of 100,000 instead of 25, for example. So, it must be comprehensible somewhere why a task was solved or decided in that certain way*." (FKB1)
Process Control	"*That I can intervene at any time*." (PKB1; A1) "*Results and decision should be regulated on the basis of what input (by the human) is given. Let me say, this is essential for me, because that's where the system bases its output on*." (FBK1)
Outcome Control	"*That I can intervene if the customer wants to make a credit line of €5,000, the AI says: That's okay. But I say: He only gets two and a half*." (PKB1) "*If the AI wants to do something automatically, as a consultant I can still veto it."* (PKB1) "*So at the end of the day I would still like to have the power to make decisions*." (FKB4)

Appendix M: Scenario within Experimental Study (Analysts; Chapter 5)

Collaborative Intelligence System Strong	**Collaborative Intelligence System Weak**
Please put yourself in the following situation.	**Please put yourself in the following situation.**
You are carrying out a risk analysis for a real estate loan in the amount of **100 000 /20 million €.** This is intended for a long-standing business client who wants to expand his production facilities with the help of the loan. You use System X[9] for the analysis.	You are carrying out a risk analysis for a real estate loan in the amount of **100 000/20 million €.** This is intended for a long-standing business client who wants to expand his production facilities with the help of the loan. You use System X for the analysis.
Recently, System X has been running on a new type of **artificial intelligence (AI)-**based, self-learning software designed to **help you with complex data analysis, so you can focus on interpreting the data**. After each interaction, you **provide feedback to the AI** on its analyses as well as the results and impact of its decisions. You have the impression that **this continuously improves the AI's decisions and thus your personal analysis results**.	Recently, System X has been running on a new type of **artificial intelligence (AI)-**based, self-learning software designed to help you with complex data analysis. However, you are not able to give the artificial intelligence direct feedback on its analyses as well as the results and effects of its decisions. **Therefore, you do not have the impression that the AI's decisions, and thus your personal analysis results, are continuously improving.**
You are able to give the system feedback via a **chatbot module**. Here, **the artificial intelligence actively asks you from time to time more precisely what you mean by your feedback**. In addition, you **can ask the system specific questions** about individual analyses.	The system also has a **chatbot module**. This is used to **transmit information** relating to the results of the artificial intelligence's analysis. You **cannot ask** the system **specific questions** about individual analyses.
You open System X and see the key figures provided by the analysis module as well as the system's risk assessment.	You open System X and see the key figures provided by the analysis module as well as the system's risk assessment.
The analysis steps that the system carries out autonomously have been defined by your institution. **You know the parameters behind them.**	The analysis steps that the system carries out autonomously have been defined by your institution. **However, you do not know the parameters behind them.**
However, you would no longer be able to calculate the key figures on your own due to the large amount of data included by the artificial intelligence. The risk assessment turns out to be slightly higher and the system suggests to not grant the loan.	Moreover, you would no longer be able to calculate the key figures on your own due to the large amount of data included by the artificial intelligence. The risk assessment turns out to be slightly higher and the system suggests to not grant the loan.
The system **asks** you via the **chatbot module** whether you agree with the risk assessment or whether you would make adjustments based on your personal assessment of the risk potential.	The system **informs you via the chatbot module** about its decision regarding the risk assessment.

[9] The name of the actual system is anonymized as it could lead back to the company the study took place.

You **have the possibility to intervene in the analysis process at any time and, for example, adjust the limits of decision parameters** (e.g., the economic equity, the operating result or the debt capacity). Likewise, you **can,** if necessary, **adjust the final decision** of the artificial intelligence on the bank lending.	However, you **have no possibility to intervene in the analysis process and, for example, adjust the limits of decision parameters** (e.g., the economic equity, the operating result or the debt capacity). Likewise, you **cannot adjust the artificial intelligence's final decision** on the bank lending.

Appendix N: Scenario within Experimental Study (Customer Advisors; Chapter 5)

Collaborative Intelligence System Strong	**Collaborative Intelligence System Weak**
Please put yourself in the following situation. A long-standing business client of yours would like to take out a real estate loan **in the amount of 100 000/20 million €** in order to expand his production facilities. In order to suggest suitable products to the customer, you open System X[10] and call up the customer's profile in the system. Recently, System X has been running on a new type of **artificial intelligence (AI)**-based, self-learning software designed to **save you time in selecting products for customers, so you can focus on the face-to-face conversation with the customer**. After each interaction, you provide feedback to the artificial intelligence on their product selection and the results and impact of their decisions. You **have the impression that this continuously improves the AI's selection, and thus your personal advisory results.** You can give the system feedback via a **chatbot module**. Here, the artificial intelligence actively asks you from time to time more precisely what you mean by your feedback. In addition, you **can ask the system specific questions** about individual product selection decisions. The system provides you with information about which credit products and suitable insurance policies make the most sense for the customer with a certain probability. The system provides this information autonomously and you would no longer be able to calculate these probabilities on your own due to the large amount of data.	**Please put yourself in the following situation.** A long-standing business client of yours would like to take out a real estate loan **in the amount of 100 000/20 million €** in order to expand his production facilities. In order to suggest suitable products to the customer, you open System X and call up the customer's profile in the system. Recently, System X has been running on a new type of **artificial intelligence (AI)**-based, self-learning software designed to **save you time in selecting products for customers**. However, you are not able to give the artificial intelligence **direct feedback** on its product selection as well as the results and impact of its decisions. Therefore, you do **not have the impression that the AI's selection, and thus your personal advisory results, are continuously improving**. The system also has a **chatbot module**. This is used to **transmit information** relating to the results of the artificial intelligence's analysis. You **cannot ask** the system **specific questions** about individual product selection decisions. The system provides you with information about which credit products and suitable insurance policies make the most sense for the customer with a certain probability. The system provides this information autonomously and you would no longer be able to calculate these probabilities on your own due to the large amount of data.

[10] The name of the actual system is anonymized as it could lead back to the company the study took place.

The selection steps, that the system carries out autonomously, were determined by your institution. **You know the parameters behind them**. The system informs you via the chatbot module about the details of the product you should offer to the customer. Moreover, it **asks** you whether you agree with the selection of the product or whether you would make adjustments based on your personal assessment of the customer. You have the **possibility to intervene in the selection process at any time and, for example, adjust the decision parameters for the product selection.** Likewise, you can, if necessary **adjust the final decision** of the artificial intelligence for the product selection.	The selection steps, that the system carries out autonomously, were determined by your institution. **However, you do not know the parameters behind them.** The system **informs you** via the chatbot module about the details of the product you should offer to the customer. However, it **does not ask you** whether you agree with the selection of the product or whether you would make adjustments based on your personal assessment of the customer. You **do not have the possibility to intervene in the selection process and, for example, adjust decision parameters**. Likewise, **you are not able to adjust the final decision** of the artificial intelligence for the product selection.

Appendix O: Questionnaire Analysts (Chapter 5)

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
Attention Checks_A			
AC_A			
AC_A_1		The amount of the loan was 100 000/ 20 million	
AC_A_2		You can provide feedback to the system, and as a result, both the artificial intelligence's decisions and your analysis results improve.	
AC_A_3		The artificial intelligence will ask you if anything is unclear and you can also ask specific questions.	
AC_A_4		You know the parameters behind the artificial intelligence analysis steps.	
AC_A_5		It is possible for you to adjust the limits of decision parameters for the decision to grant credit.	
AC_A_6		It is possible for you to adjust the final decision to the artificial intelligence.	
Perceived Competence			
PComp_A			
PComp_A_1	I felt very competent in this game.	I feel like I competently mastered the task described in the text.	Radel, Pelletier, and Sarrazin (2011)
PComp_A_2	I felt able to meet the challenge of performing well in this task.	I feel like I have mastered the task described in the text well.	
PComp_A_3	I was able to master this task.	I have mastered the task described in the text.	
PComp_A_4	I was good at doing this task.	I have finished the task described in the text well.	
Perceived Cognition	Definition Bradley et al (2010): They want information so that they are able to explain past occurrences, interpret ongoing events, predict future occurrences, and make plans to act accordingly. They want to minimize ambiguity and uncertainty. They do not want to feel ignorant, confused, or bewildered by what is going on in the service encounter		
PCog_A			
PCog_A_1		I feel like I know exactly how the process of making that decision was done.	SELF GENERATED based on definition
PCog_A_2		I feel like I know exactly how the outcome of the process came about.	
PCog_A_3		I feel like I could explain the results of the process.	
PCog_A_4		I feel like I could explain the process of the decision making.	
PCog_A_5		I feel like I'm overlooking the future developments that come with the decision I've made.	
PCog_A_6		I feel like I can follow the processes in the scenario exactly.	
Perceived Justice			
PJust_A			
PJust_A_1	How fair were the procedures used to set your goal?	The measures taken to design the cooperation with the AI in the scenario are fair.	Elkins (2000)
PJust_A_2	How fair were the procedures used to determine your goal?	I find the decision-making process in the scenario to be fair.	

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
PJust_A_3	How fair were the procedures used to set your goal?	Overall, I find the process of working with the artificial intelligence in the scenario to be fair	
PJust_A_4		The results of the collaboration with artificial intelligence in the scenario were created through a fair process.	SELF GENERATED
Perceived Control			
PCon_A			
PCon_A_1	‘‘To what extent do you feel that you can influence the quality of the service that you receive?’’	I feel like I can influence the quality of the artificial intelligence‘s output	Yagil and Gal (2002)
PCon_A_2	‘‘To what extent do you have the freedom to choose the way in which you receive the service (e.g., place, time,duration)?’’;	I feel that I can decide in what way I receive support from the artificial intelligence (e.g., when and in which cases).	
PCon_A_3	‘‘To what extent do you feel that you can affect the service worker’s behavior?’’	I feel like I can influence how the artificial intelligence works.	
PCon_A_4		I have the feeling, that I can control the decision-making process in the scenario.	SELF GENERATED
Perceived Responsibility			
PResp_A			
PResp_A_1	#1 How responsible do you feel for the outcome of this choice?	How responsible do you feel for the ultimate lending decision when the AI-based system does the analysis?	Jörling et al. (2019)
PResp_A_2	#2 How accountable do you think you are for the outcome of this choice?	To what extent do you think you are accountable for lending decisions?	Jörling et al. (2019)
PResp_A_3	# 3To what extent did you feel in control of the outcome of this choice?	To what extent do you feel responsible for making decisions about lending money or not?	Jörling et al. (2019)
PResp_A_4	Do you personally feel responsible for what you have just done?	To what extent do you feel personally responsible for the lending decision?	Gosling, Denizeau, and Oberle (2006)
Manipulation Checks			
MC_A			
MCAmount_A_1		How do you evaluate the amount of the real estate loan?	
MCColla_A_2		How collaborative would you describe the AI depicted in the scenario? *(Info: In this context, collaborative means that the AI acts concerted and involves you in the fulfillment of the task. The system uses its abilities to achieve the common goal (correct decision about the loan) in collaboration with you and your abilities.)*	
MCEnh_A_3		How would you rate the mutual improvement of both yours and the AI's results through your collaboration depicted in the scenario?	
MCEng_A_4		How would you rate the extent to which the AI represented includes you in the process of completing the task?	

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
MCTra_A_5		How would you rate the transparency of the AI depicted in the scenario?	
MCPCon_A_6		How would you rate the amount of control you had over the process of making decisions in the scenario?	
MCO-Con_A_7		How would you rate the amount of control you had over the final decision in the scenario?	
Realism & Complexity Checks			
RC & CC			
RC_A		I think the scenario is realistic.	
CC_A		I could easily put myself into the described scenario.	
Demografics			
Age_A		Please indicate your birth year	
Gender_A		Please indicate your gender	
Education_A		Please indicate your highest degree	
Tenure_A		Please indicate how long you have been working in your job	
Tenure_CC_A		Please indicate how many years you have been working for your current company	
Region_A		Please indicate the state you are working in	

Appendix P: Questionnaire Customer Advisors (Chapter 5)

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
Attention Checks			
AC_K			
AC_K_1		The amount of the loan was 100 000/ 20 million	
AC_K_2		You can provide feedback to the system, and as a result, both the artificial intelligence's decisions and your consulting results improve.	
AC_K_3		The artificial intelligence will ask you if anything is unclear and you can also ask specific questions.	
AC_K_4		You know the parameters behind the artificial intelligence product selection steps.	
AC_K_5		It is possible for you to customize decision parameters for product selection.	
AC_K_6		It is possible for you to adjust the final decision to the artificial intelligence.	

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
Perceived Competence			
PComp_K			
PComp_K_1	I felt very competent in this game.	I feel like I competently mastered the task described in the text.	Radel, Pelletier, and Sarrazin (2011)
PComp_K_2	I felt able to meet the challenge of performing well in this task.	I feel like I have mastered the task described in the text well.	
PComp_K_3	I was able to master this task.	I have mastered the task described in the text.	
PComp_K_4	I was good at doing this task.	I have finished the task described in the text well.	
Perceived Cognition	Definition Bradley et al (2010): They want information so that they are able to explain past occurrences, interpret ongoing events, predict future occurrences, and make plans to act accordingly. They want to minimize ambiguity and uncertainty. They do not want to feel ignorant, confused, or bewildered by what is going on in the service encounter		
PCog_K			
PCog_K_1		I feel like I know exactly how the process of making that decision was done.	SELF GENERATED
PCog_K_2		I feel like I know exactly how the outcome of the process came about.	
PCog_K_3		I feel like I could explain the results of the process.	
PCog_K_4		I feel like I could explain the process of product selection.	
PCog_K_5	.	I feel like I'm overlooking the future developments that come with the product choices I've made.	
PCog_K_6		I feel like I can follow the processes in the scenario exactly.	
Perceived Justice			
PJust_K			
PJust_K_1	How fair were the procedures used to set your goal?	The measures taken to design the cooperation with the AI in the scenario are fair.	Elkins (2000)
PJust_K_2	How fair were the procedures used to determine your goal?	I find the decision-making process in the scenario to be fair.	Elkins (2000)
PJust_K_3	How fair were the procedures used to set your goal?	Overall, I find the process of working with the artificial intelligence in the scenario to be fair	Elkins (2000)
PJust_K_4	The results of the collaboration with artificial intelligence in the scenario were created through a fair process.	The results of the collaboration with artificial intelligence in the scenario were created through a fair process.	SELF GENERATED
Perceived Control			
PCon_K			
PCon_K_1	‘‘To what extent do you feel that you can influence the quality of the service that you receive?’’	I feel like I can influence the quality of the artificial intelligence‘s output	Yagil and Gal (2002)
PCon_K_2	‘‘To what extent do you have the freedom to choose the way in which you receive the service (e.g., place, time,duration)?’’;	I feel that I can decide in what way I receive support from the artificial intelligence (e.g., when and in which cases).	
PCon_K_3	‘‘To what extent do you feel that you can affect the service worker’s behavior?’’	I feel like I can influence how the artificial intelligence works.	
PCon_K_4		I have the feeling, that I can control the decision-making process in the scenario.	SELF GENERATED
Perceived Responsibility			

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
PResp_K			
PResp_K_1	#1 How responsible do you feel for the outcome of this choice?	How responsible do you feel for the ultimate product choice when the AI-based system does the analysis?	Jörling et al. (2019)
PResp_K_2	#2 How accountable do you think you are for the outcome of this choice?	To what extent do you think you are accountable for the product choices?	
PResp_K_3	# 3To what extent did you feel in control of the outcome of this choice?	To what extent do you feel responsible for making decisions about the product choice?	
PResp_K_4	Do you personally feel responsible for what you have just done?	To what extent do you feel personally responsible for the decision on product offered?	Gosling, Denizeau, and Oberle (2006)
Manipulation Checks			
MC_K			
MCAmount_1		How do you evaluate the amount of the real estate loan?	
MCColla_K_2		How collaborative would you describe the AI depicted in the scenario? *(Info: In this context, collaborative means that the AI acts concerted and involves you in the fulfillment of the task. The system uses its abilities to achieve the common goal (correct decision about the product selection) in collaboration with you and your abilities.)*	
MCEnh_K_3		How would you rate the mutual improvement of both yours and the AI's results through your collaboration depicted in the scenario?	
MCEng_K_4		How would you rate the extent to which the AI represented includes you in the process of completing the task?	
MCTra_K_5		How would you rate the transparency of the AI depicted in the scenario?	
MCPCon_K_6		How would you rate the amount of control you had over the process of making decisions in the scenario?	
MCOCon_K_7		How would you rate the amount of control you had over the final product selection in the scenario?	
Realism & Complexity Checks			
RC & CC			
RC_K		I think the scenario is realistic.	
CC_K		I could easily put myself into the described scenario.	
Demografics			
Age_K		Please indicate your birth year	
Gender_K		Please indicate your gender	

Item label	Original item English (if applicable)	Adapted item translated to English from German	Reference
Education_K		Please indicate your highest degree	
Tenure_K		Please indicate how long you have been working in your job	
Tenure_CC_K		Please indicate how many years you have been working for your current company	
Region_K		Please indicate the state you are working in	

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Appendix Q: Overview of Experimental Groups (Chapter 5)

	Analysts		***Customer Advisors***	
	Collaborative Intelligence		**Collaborative Intelligence**	
Loan Amount	Strong	Weak	Strong	Weak
20 Mio.	Group 1 n = 41	Group 3 n = 50	Group 1 n = 25	Group 3 n= 31
100 k.	Group 2 n = 46	Group 4 n = 48	Group 2 n = 34	Group 4 n = 34

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