Consumer Responses to Service Robots

From Pre-Interaction to Post-Interaction

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Abstract

Although robots are increasingly being deployed in service industries, the field of research pertaining to consumer responses to service robots remains insufficient. This dearth of knowledge and understanding has the potential to hinder the widespread adoption of service robots and the successful implementation of robotic service (r-service). This dissertation answers the following research question: How do consumers respond to service robots regarding their emotion, cognition, and behavioral intention from pre-interaction to post-interaction with these robots?

Paper 1 focuses on how perceived comfort with robots penetrates consumers’ implicit social decision-making (trust) and affects consumer responses. This study is motivated by a scarcity of knowledge on user pre-interaction perception and reaction to service robots. To bridge this gap, this paper cartographically investigates the effect of the mechatro-humanness degree of robots on users’ perceived comfort with robots, disentangling the underlying mechanism of human–robot trust. The findings provide tools for future studies on social–psychological and affective factors that could inform the design of socially competent robots.

Whereas studies regarding what drives consumers to use service robots have offered fragmented results, Paper 2 launches a conceptual framework to comprehend the literature and obtain an in-depth understanding of individual attitudes and intentions to use service robots. Drawing on a triangulation of three perspectives on end-users in adoption research, this framework adopts technology acceptance theories, service quality, and expectancy-value theory to set up the skeleton of the framework. The antecedents of service robot acceptance are subdivided into robot design, consumer-oriented, relational components, and exogenous factors. The paper not only elaborates on the present situation of service robot acceptance research but also promotes the literature by developing a comprehensive framework regarding the effect factors.

Paper 3 is motivated by a lack of well-developed studies sorting out the antecedents that affect consumer evaluation of r-service. This paper seeks to develop an r-service quality scale. I conducted a systematic literature review on r-service quality evaluation, thereby identifying the indicators of r-service dimensions and potential methodological issues of developing measurement instruments. The deliverables are strategically relevant for business operations of r-services.

Drawing from the view of functional adaptivity, Paper 4 investigates how service heterogeneity affects consumer post-interaction responses to r-service by differentiating satisfying and dissatisfying service situations. This paper delineates the effects of different service providers and the inclusion of prior r-service experience on r-service heterogeneity. The findings offer theoretical and practical implications by answering the call for more research on r-service, broadening the understanding of the business value of artificial intelligence innovations and their relation to human responses.

Keywords: Service robot; Comfort with robots; Robotics adoption; Service quality; Heterogeneity

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Preface

As the sands of time have flowed by, the expedition that encapsulated my doctoral voyage now draws to a close, prompting a moment of profound reflection upon the odyssey as a whole. In retrospect, I find myself characterizing this five-year journey as a self-imposed exile – a deliberate divergence from the tranquil shores of comfort, a conscious immersion into the boundless pursuit of scientific truth. In this seclusion, I not only acclimated to solitude but also tended to the flame of perseverance that burns within. Yet, this self-imposed exile has undergone a remarkable transformation, etching an indelible chapter into the fabric of my existence. It has ignited an ardent ambition to secure my place as a recognized scholar, driven by the experiences encountered along this path. Throughout this journey, I have been exceedingly fortunate to find solace and strength through the support and encouragement extended by a multitude of remarkable individuals and esteemed institutions.

Foremost among these, my heartfelt gratitude extends to my main supervisor, Associate Professor Yong Liu. Spanning back to the inception of my research voyage over seven years ago, during my time as a master’s student, his unwavering support has remained a guiding beacon. He not only kindled the flames of my passion for exploration but also stood steadfast, ever-ready, to illuminate my path with wisdom. My very presence here today stands as a testament to the immeasurable value of his continuous guidance and assistance.

To my co-supervisor, Professor Virpi Kristiina Tuunainen, I owe a profound debt of gratitude for her exceptional mentorship throughout the trajectory of my Ph.D. expedition. The symphony of knowledge and insights we jointly composed has stood as the cornerstone of my academic journey. Without her benevolent support, the fruition of this dissertation would have been but a distant mirage. As a remarkable female scholar, she stands as an inspiring role model from whom I have gleaned invaluable inspiration through the tapestry of academia.

I must extend my heartfelt appreciation to the pre-examiners, Professor Thomas Hess and Professor Kari Smolander, whose constructive critiques and invaluable feedback have not only fortified the foundation but also sculpted this dissertation into its most refined and polished form. I also feel immensely privileged that I will have Associate Professor Henri Pirkkalainen as the distinguished opponent for the public defense.

With sincere appreciation, I extend my gratitude to the benefactors of my academic pursuits—the Foundation for Economic Education (Liikesivistysrahasto), the Marcus Wallenberg Foundation, and the HSE Support Foundation. Their generous support has undoubtedly fortified my endeavors. Equally, I am indebted to the visionary leaders of the Department of Information and Service Management, Professor Markku Kuula and Professor Matti Rossi, for fostering an environment conducive to scholarly growth. My acknowledgments extend to encompass Associate Professor Esko Penttinen, Associate Professor Riitta Hekkala, Assistant Professor Hadi Ghanbari, Principal University Lecturer Dr. Johanna Bragge, Dr. Kari M. Koskinen, Dr. Niina Mallat, and a myriad of esteemed individuals whose contributions have been pivotal.
The administrative allies within the Department of Information and Service Management and the Doctoral Programme of Aalto University School of Business—including the dedicated efforts of Merja Mäkinen, Hanne Lehtinen, Tiina Kotti, and all other members—merit my heartfelt gratitude for their unwavering commitment.

I pause to pay tribute to my esteemed co-author, Associate Professor Hongxiu Li, for her collaborative spirit that has enriched the tapestry of this work. My lovely colleagues, especially Yuting Jiang, Lin Chen, Linyu Liu, Zhiqiang Liao, Alexandra Petrova, and Dr. Wenjie Fan, have been steadfast companions on this exhilarating journey, their camaraderie serving as an unceasing source of inspiration.

To my dearest friends—Dr. Wenzhong Zhang, Jiawei Zhang, Junjie Yin, Xiaoxu Liu, Dr. Sheng Dai, Mei Yang, Yunhui Zhou, Aleksandr Namanyuk, Dr. Jiale Huo, Dr. Qiang Yang, Dr. Siwei Zou, Dr. Mingyang Zhang, Cong Liu, and Wanying He — your enduring presence has been a soothing sanctuary, a respite from the solitude that sometimes accompanies distant journeys. And to my cherished friend of 15 years, Dr. Xun Mu, our high school bond has been an unyielding wellspring of strength, an unwavering beacon that has guided me through both the trials and triumphs of life.

My gratitude transcends generations, flowing back to my family, particularly my parents and my sister, whose unwavering support and boundless encouragement have been my bedrock. Lastly, and profoundly, this dissertation is dedicated to my beloved partner, Dr. Xun Zhou. You are not only my confidant but also the steadfast ally who spurs me toward the pinnacle of achievement. You complete this journey. With hearts brimming with gratitude, we mark the end of this chapter, embracing the unknown horizons that beckon us forward.

York, UK, August 2023

Yanqing Lin
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List of Publications

This doctoral dissertation consists of a summary of the following research papers, which are referred to in the text by their numerals.


Author’s Contribution

**Paper 1: Understanding Pre-interaction Responses to Humanoid Robots: A View of Comfort with Robots**

Yanqing Lin was the lead author of this paper, taking the lead in writing the manuscript under the supervision of Yong Liu and Virpi Kristiina Tuunainen. She conceived the empirical study; contributed to the design and implementation of the research; and was responsible for collecting, coding, analyzing, and interpreting data. Yong Liu and Virpi Kristiina Tuunainen both supervised the overall work on the research and writing of the manuscript, contributed to the design of the main conceptual constructs, and brought their expertise to the data’s methodological analysis and the quality of the presentation of the findings.


Yanqing Lin was the sole author of this paper.

**Paper 3: Instrument Development for R-Service Quality: A Literature Review**

Yanqing Lin was the sole author of this paper.

**Paper 4: Consumer Responses to Robotic Services: A View of Service Heterogeneity**

Yanqing Lin was the lead author of this paper. She took the lead in writing and revising the manuscript and was responsible for collecting, coding, processing, and interpreting data. Lin also contributed to the design and implementation of the research, and she designed the tables and figures. Yong Liu conceived the study, contributed to the data collection and analysis, and supervised the overall writing of the manuscript. Virpi Kristiina Tuunainen, Xun Zhou, and Hongxiu Li contributed to the theoretical framework, aided in the conceptualization of the study, enhanced the quality of the presentation of findings, and participated in the development of the data structure. Feng Hu contributed to the data collection and the quality of the presentation of findings.
1. Introduction

“The robots are coming, whether we like it or not, and will change our economy in dramatic ways.”

—Kristen Soltis Anderson

With robotics penetrating our social sphere (Breazeal, 2003; Zhao, 2006), human–robot interaction (HRI) has been increasingly social with users in more casual intuitive approaches (Fong et al., 2002; Mathur and Reichling, 2016). Against this backdrop, robotics and artificial intelligence (AI) have been bursting into the service sector in recent years, finding expression in the rapid rise of service robots. Notably, service robots are typically conceptualized as computer-guided technological innovations capable of performing physical tasks and operating autonomously without explicit instructions (Colby et al., 2016; Tussyadiah, 2020; Wan et al., 2021). In this context, robotic service (r-service) comprises the customer service experience delivered by service robots.

According to recent statistics (Market Research, 2020), the service robot market is snowballing, having been projected to grow at a compounded annual growth rate of approximately a quarter and surpass 102.5 billion US dollars by 2025. Furthermore, the COVID-19 pandemic further sped up the drive for the unprecedented relevance of robotics to service sectors because using robots in service delivery can decrease the human touch (Kim et al., 2021; Matthews, 2020; Romero and Lado, 2021). Industries such as education (Park & Kwon, 2016), hospitality (de Kervenoael et al., 2020; Zhong, Sun, et al., 2020), tourism (Ivanov and Webster, 2019; Li et al., 2013), and restaurant (Lu et al., 2021; Morita et al., 2020) have been earlier adopters of robots in service encounters. For instance, the use of service robots is progressively becoming popular in customer-facing roles because of their competence in working collaboratively alongside human personnel (van Doorn et al., 2017) and interacting with customers for value cocreation for various service purposes (Čaić et al., 2019). As such, the service robot has increasingly been viewed as an element integrated into the customer frontline experience (Ivanov et al., 2018; Tussyadiaha and Parkb, 2018; Wan et al., 2021).

The proliferation of the robot workforce in service encounters highlights the importance of understanding either facilitators and barriers or the opportunities and threats of integrating service robots into regular business operations, including how consumers respond to service robots and evaluate r-services (e.g., Belanche et al., 2020a; Kuo et al., 2017; Tussyadiaha and Parkb, 2018). Here, r-service has been announced to be an essential and integral part of the consumer experience (Tung and Law, 2017). Whereas the current literature contends that human-like service robots may develop solid emotional attachments, such as customer delight (Mende et al., 2019) and satisfaction (Ho et al., 2020; Yang and Chew, 2020), they could also “elicit greater consumer discomfort (i.e., eeriness and a threat to human identity)” (Mende et al., 2019, p. 535). In this context, the information systems (IS) community has called for research to understand customer responses to the r-service (see, e.g., Diederich et al., 2022; Noble and Mende, 2020; Paluch and Wirtz, 2019). In particular, this has included a greater examination of the importance of understanding user responses to a robot either cognitively or emotionally (Mathur and Reichling, 2016). Practitioners have also increasingly placed
emphasis upon how to incorporate robotics into daily business operations to improve service quality and launch better service experiences for customers (Lu et al., 2020; Wirtz et al., 2018).

Accordingly, the present dissertation aims to answer the following research question: How do consumers respond to service robots? Specifically, I strive to explain consumers’ cognitive, emotional, and behavioral responses to service robots before and after interacting with them. The current dissertation investigates i) how pre-interaction (i.e., before interacting with robots) perceptions, such as perceived comfort with robots, instill customers’ trust in robots and affect consumer adoption decision of service robots; ii) what factors facilitate or prevent consumers from accepting service robots; iii) how customers evaluate the r-service that they receive; and iv) how post-interaction (i.e., after interacting with robots) perceptions of r-services, such as perceived service heterogeneity, affect consumers’ loyalty (revisit intentions) of the r-service.

The present dissertation offers several academic contributions to robotics-oriented research in the IS discipline. First, my dissertation revisits and relaunches IS assumptions of user–system interaction, particularly when the service robot challenges conventional IS assumptions. Conventional IS assumptions indicate that users are aware of their unilateral interactions with a system and that the system should offer consistent and transparent functionality and be independent of the situated environment (Benbasat and Zmud, 2003; Demetis and Lee, 2018; Schuetz and Venkatesh, 2020). Notably, the conventional IS perspective considers technological artifacts as tools for solving problems and/or offering services to users (Benbasat and Zmud, 2003; Demetis and Lee, 2018; Schuetz and Venkatesh, 2020). This perspective endorses a clear-cut one-sided relationship between users and technological artifacts, where users enter specific information/data into a system through a user interface (UI), and the system produces outcomes based on predesigned computation. That is, the user is seen as the initiator of the process, while the technological artifact is seen as the passive recipient of the inputs. However, these assumptions are no longer applicable to r-services, considering that service robots exhibit several novel capabilities, such as mimicking human cognitive abilities to initiate more human-like bilateral interactions (Madakam et al., 2019; Schuetz and Venkatesh, 2020; Stückler et al., 2016). Second, given the AI-enabled r-service as an unprecedented social phenomenon, my dissertation aims to introduce new views, such as comfort theory and the lens of service heterogeneity, in the r-service context of novelty to extend the current knowledge of consumer responses to service robots and r-services. Third, my dissertation enriches the literature by reaching a holistic picture presenting consumer responses to r-service penetrating the overarching phases covering pre-interaction, robotics adoption, r-service quality assessment, and post-interaction with robots.

Managerial implications in cooperating with robotics in the daily operations of service industries can also be drawn from the present dissertation. First, the research findings can help the manufacturing sector of service robots with robot design to enhance r-service quality by fulfilling customer requirements, as well as elicit positive customer attitudes toward r-service. Second, this dissertation may offer valuable insights for service practitioners to deploy service robots in their business operations effectively, which can not only liberate intensive labor reliance and facilitate management efficiency but also improve r-service delivery performance.
1.1 Objectives and Research Questions

The objective of the current dissertation is to provide new knowledge for understanding consumer responses to service robots from the pre-interaction to the post-interaction phase. In general, the present dissertation strives to answer the overarching research question (RQ):

**RQ**: How do consumers respond to service robots?

To address this research question, I investigated how consumers respond to service robots in terms of emotion, cognition, and behavioral intention, focusing on a better understanding of the holistic picture depicting consumer responses to service robots from pre-interaction to post-interaction with robots. The present dissertation provides strategic insights for the global robot industry to design complementary products for consumers and deliver value for various business stakeholders by leveraging the benefits of the upcoming robot economy. To this end, I break down the overarching question and discuss it from the perspectives of pre-interaction, robotics adoption, r-service quality evaluation, and post-interaction. Five corresponding main subresearch questions framing the dissertation are used:

- **RQ1**: How does anthropomorphism affect comfort with robots and social decision-making?
- **RQ2**: How does comfort with robots affect humans’ social decision-making and adoption decisions?
- **RQ3**: What facilitates consumers’ acceptance of service robots?
- **RQ4**: How do consumers evaluate the r-service they receive?
- **RQ5**: How does the perceived service heterogeneity of r-services affect consumer intentions to revisit the service?

Four standalone research papers are included in this dissertation to answer these subresearch questions. Specifically, the present dissertation examines RQ1 and RQ2 in Paper 1, RQ3 in Paper 2, RQ4 in Paper 3, and RQ5 in Paper 4. The linkage between the four papers is illustrated in Figure 1.
1.1.1 Paper 1

From the perspective of pre-interaction with service robots, Paper 1 focuses on employing comfort theory to explain end-user responses to robotic anthropomorphism from observing service robots. Motivated by a lack of knowledge about user perception and reaction to service robots prior to interacting with robots, this study disentangles how perceived comfort with robots, which is a pre-interaction perception triggered by robotic anthropomorphism, penetrates users’ implicit social decision-making and affects their responses. Accordingly, Paper 1 asked the following, “RQ1: How does anthropomorphism affect comfort with robots and social decision-making?” “RQ2: How does comfort with robots affect humans’ social decision-making and adoption decisions?”

To answer these two research questions, the study first developed and verified dimensional construct measurements for comfort with robots by drawing on comfort theory. Then an image sample pool consisting of 80 real-world robot images was created, based on which the anthropomorphism spectrum was quantified. The empirical data were collected through a scenario-based survey, in which the respondents were required to fill out the survey questionnaire based on observing the randomly assigned robot image. This allowed me to determine the perceived valence and magnitude of comfort with the displayed robots, investigate the relationship between anthropomorphism and comfort with robots, and explore the impact of comfort with robots on robot adoption decisions through human–robot trust.

To this end, the present study is among the pioneering attempts to cartographically investigate the Uncanny Valley (UV)-resemblance effect of the degree of robot anthropomorphism on consumers’ perceived comfort with robots, creating a valuable background for future research to theorize r-services. In addition, perceived comfort with robots appears to be a more appropriate measure than constructs such as likeability when evaluating a robot approaching a user for service delivery. Given that comfort with robots lays the basis for understanding how humans perceive and react to humanoid-appearing robots, the present study addresses the effect mechanism of humans’ implicit social decision-making (human–robot trust). Furthermore, the proposed innovative methods of assessing human social perceptions of humanoid robots concerning their degree of anthropomorphism provide tools for future studies into the social-psychological and affective elements that can inform robot design.

1.1.2 Paper 2

From the view of robotics adoption, Paper 2 establishes a conceptual framework to comprehend the current knowledge and gain an in-depth understanding in terms of customer attitudes and their intention to (re)use service robots. Although an increasing number of studies have been involved in robotic adoption research, these studies regarding what drives consumers to use service robots remains fragmented. To bridge this gap, this study asked, “RQ3: What facilitates consumers’ acceptance of service robots?”

To address this research question, I conducted an extensive literature review and a content analysis. As a result, a conceptual framework covering the determinants of service robot acceptance that were considered in previous studies was built. Concretely, inspired by the
triangulation of three perspectives on end-users in adoption research, that is, technology user, consumer, and network member, the framework employs technology acceptance theories, SERVQUAL, and expectancy-value theory to build the skeleton of the framework. The antecedents affecting customer acceptance of service robots can be categorized into four groups: robot-design components, consumer-oriented components, relational components, and exogenous factors. The present study is among the first to structure a comprehensive framework by integrating the current knowledge of service robot adoption, which offers valuable insights for business practitioners in terms of designing and deploying service robots.

1.1.3 Paper 3

Driven by the desire to develop the conceptualization or measurement of r-service quality, Paper 3 aims to develop an r-service quality scale from the service evaluation view. Compared with conventional digital services (e.g., self-service technology), human-like interactions and emotional elements may affect consumer responses to service robots, resulting in differentiated facilitators and barriers to tackling r-services. The importance of developing systematic scales concerning the dimensions driving or thwarting consumers to adopt r-services is further emphasized. However, a lack of studies sorts out the antecedents affecting consumer evaluation of r-service. By instrumenting r-service quality, the present study addresses the following question “RQ 4: How do consumers evaluate the robotic service they receive?”

To settle the research question, I first conducted a systematic literature review on consumer evaluations of r-service, thereby identifying the indicators of r-service dimensionality. By reviewing the literature, the present study reports the current knowledge on r-service quality instruments by identifying the dimensionality of r-service evaluation and discussing potential methodological issues and limitations of existing studies in developing measurement scales of r-service quality. In the vein, the present study has the potential to expand the existing IS literature on evaluating r-services. More importantly, the deliverables of the study are strategically relevant for any business operations of r-service, as well as for the providers of service robots because using such a measurement instrument allows them to examine consumer perception mechanisms, thereby taking possible practical actions to tackle the identified perceptual problems.

1.1.4 Paper 4

From the post-interaction view, Paper 4 is motivated by the fact that AI-based robots are being increasingly deployed in service sectors, but little is known about how users respond to the novel r-service compared with traditional digital service. To bridge this research gap, the study answers the following question “RQ 5: How does the perceived service heterogeneity of r-services affect consumer intentions to revisit the service?”

As an essential capability of AI robots, functional adaptivity refers to the ability to adapt their behavior to various service situations and tasks based on the situated environment and information that the robots receive (Schuetz and Venkatesh, 2020). Functional adaptivity enables robots to operate in complex and dynamic settings and to perform various service tasks. This study draws from the perspective of functional adaptivity, investigating the antecedents and effects of service
heterogeneity on consumer responses to service robots by differentiating satisfying and dissatisfying service situations. The arguments are proposed for four reasons. First, the existing literature on user responses to service robots ignores the functional features of service robots. Second, functional adaptivity in service robots can lead to service heterogeneity in r-service, which has received little attention in the IS literature. Third, past IS studies have placed an emphasis on the role of previous experience in technological artifact use, but its role in the context of r-service remains to be further investigated. Fourth, previous studies stress that consumers respond differently to service success and service failure.

To answer the research question, two studies were designed and conducted to triangulate the research findings. Study I included scenario-based experiments (with 2 × 2 service scenarios) involving both inexperienced consumers and experienced consumers in a predesigned hotel reception service context. Study II (with two service situations) aimed to triangulate the research findings in Study I by conducting a field study that took various real-life service settings into account.

Paper 4 has offered a theoretical account to understand the unique nature of r-service by highlighting the functional adaptivity and unstructured inputs of r-service compared with the functional transparency and structured inputs of conventional digital services. As such, the theoretical account establishes a solid basis for studying r-service from the view of heterogeneity, which can be further extended to understand r-service from other aspects, such as trust development. In addition, this study developed and refined a measurement scale of service heterogeneity based on a systematic process of instrument development, which may provide a useful tool for future studies on service heterogeneity. By demonstrating the impact of prior r-service experience on r-service heterogeneity, this study highlights the importance of personal features in affecting the r-service perceptions of end-users. Furthermore, this study elaborates on the variety of effects of service heterogeneity on revisit intention, here contingent on (satisfying or dissatisfying) service situations, which enrich the contemporary knowledge subscribing the negative effect of heterogeneity in human-delivered services.

1.2 Thesis Structure

The present dissertation is composed of two parts.

The first part presents a summary of the research conducted to address the research questions previously outlined. In the following, I will first position this dissertation within the IS discipline in Chapter 2 by reviewing the literature of relevance to identify the research gaps. Then, I will summarize the four papers included in Chapter 3, present the research methodology, and discuss the findings according to the specific research questions. Finally, I will elaborate on the implications for research and practice and sum up the contributions of the dissertation and the limitations.

The second part of this dissertation consists of four original research papers, hence offering full accounts of the research projects conducted for my dissertation.
2. Literature Review and Theoretical Background

In this chapter, I have reviewed the literature and positioned this dissertation in relation to the literature to illustrate how my studies can advance the current knowledge regarding consumer response to service robots from the IS standpoint. First, I have elaborated on how service robots are different from conventional IS entities and challenge traditional IS assumptions by reviewing the literature. Then, an extensive literature review is presented based on the research in terms of how users respond to service robots or r-services.

2.1 Service Robots: Challenges to Render into Conventional IS Assumptions

Service robots can partially or fully autonomously interact, communicate, and deliver services to human beings (International Federation of Robotics, 2021). Service robots are capable of autonomously acting in the physical world by ‘perceiving’ the situated circumstances and adapting their actions in service delivery situations. Service robots can be virtual (e.g., online chatbots) or with a physical presence (e.g., robotic entities deployed in the hotel reception desk and restaurants). In the present dissertation, however, the conceptualization of service robots excludes virtual robots with no physical presence.

AI-based service robots are a new class of innovations that implement human-like capabilities. Unlike previous technological advancements that make systems more powerful, connected, and mobile, the advent of service robots marks a uniquely disruptive advance aimed at making machines more human-like (Schuetz and Venkatesh, 2020), both in terms of cognitive abilities and anthropomorphic design, such as appearance and gestures. The deployment of robots in service sectors represents a transition from user–system interactions in conventional digital services or consumer–producer interactions in human-delivered services to HRI in r-services.

Fuelled by AI, service robots fundamentally challenge traditional IS beliefs. HRI presents several new features distinct from user–system interactions. For instance, systems act as tools with consistent functionality to generate specific outcomes by operating on specific inputs (Benbasat and Zmud, 2003; Schuetz and Venkatesh, 2020). Users usually develop emotional and/or cognitive reactions after using conventional digital agents (e.g., online recommendation systems). However, users tend to develop initial perceptions by observing service robots. That is, users’ perceptions of service robots can be formed, regardless of their functionality before interacting with them by observing their physical presence (Eveleth, 2013; Haring et al., 2013; Koay et al., 2006). In this vein, user responses to a robot begin to be shaped before actual interactions with robots, which is the so-called pre-interaction. These responses from observing robots’ physical presence are unique to robots compared with conventional digital service agents that are intangible in nature.

Furthermore, service robots dramatically blur the boundaries between the clear-cut fronts of human capabilities and those of digital agents (e.g., computers). Driven by AI, service robots are capable of performing various human feats, such as cognition and learning with significant implications (Schuetz and Venkatesh, 2020). The equipment of cognitive capabilities makes service robots no longer limited to machine ability, hence entering the realm of human ability. As an example, Sophia (HansonRobotics, 2019), Hanson Robotics’ most advanced human-like robot,
can establish emotional connections and launch meaningful conversations with people using natural speech. Users no longer need to rely on a UI (e.g., phone screen) but can instead interact with a machine as they would with any other human being (Schuetz and Venkatesh, 2020). In this vein, the conventional IS assumptions may no longer be applicable in the context of service robots, which presents us with an opportunity to explore the boundary conditions of the existing knowledge and launch new theoretical contributions to the IS discipline.

Against this backdrop, the present dissertation delves into the singular chance that service robots present to the IS field. In particular, I examine how the unique capabilities of service robots challenge the conventional IS assumptions that underlie research on user–system interaction. By exploring the underlying assumptions and limitations of existing research, I establish a more comprehensive and nuanced understanding of the capabilities of service robots and the implications of their use. The significance of this part lies in its potential to expand our understanding of the complex interplay between humans and robots, along with the ways in which AI technology can be leveraged to enhance and transform IS research.

2.1.1 Pre-interaction Perception Development

The success of HRI is highly contingent on the user acceptance of the technology (Davids, 2002), which is closely linked to user response to robots, including pre-interaction responses. As mentioned above, users tend to shape their cognitive or emotional perceptions of a robot before interacting with the robot by observing the robot’s physical presence (e.g., Eveleth, 2013; Haring et al., 2013; Koay et al., 2006). As such, users’ pre-interaction responses to a service robot are largely attributed to the visual cues of the robot, such as robot appearance, gestures, and movement. Appendix A lists the key empirical literature on users’ responses to the characteristics of service robots.

The present literature regarding end-user responses to robots underlines the effect of robots’ attributes of physical presence. Robotic anthropomorphism and its influence on users’ responses are among the most extensively discussed topics in the recent HRI literature. Anthropomorphism refers to the tendency to attribute human-like characteristics, intentions, and behaviors to non-human subjects (Laksmidewi et al., 2017). Similar terminologies, for example, humanness (Amelia et al., 2022; Fernandes & Oliveira, 2021; Mele et al., 2020), humanoid (Choi et al., 2021; Qiu and Benbasat, 2009), and human-likeness (Lu et al., 2021) have been investigated as well in past studies. Despite the significant advancement in robotics, hominine robots cannot imitate human behavior perfectly so far. It is well known that human reactions to imperfect hominine robots are very complicated (Mathur and Reichling, 2016; Schuetz and Venkatesh, 2020). Among all the employed theoretical lenses that interpret the relationship between robot appearance and human reactions, the uncanny valley hypothesis (UVH) can be the one that attracts the most attention from both academia and practitioners (Blut et al., 2021; Mathur and Reichling, 2016). UVH highlights an “Uncanny Valley Effect” (UVE), which means “In climbing toward the goal of making robots appear human, our affinity for them increases until we come to a valley” (Mori, 1970, p. 34). Note that UVH posits a non-linear relationship between how much a robot resembles a human and emotional reactions to the robot.
Anthropomorphism has been endorsed as a significant factor in robot adoption, one that can directly affect users’ attitudes and willingness to (re)use service robots. However, a dispute has been found in the literature on the relationship between robotic anthropomorphism and user responses. Specifically, Tussyadiah and Parkb (2018) concluded a positive association between anthropomorphism and the adoption intention of hotel service robots. Chuah et al. (2021) validated the importance of human-likeness in fulfilling consumers’ intent to use service robots. Similarly, Lu et al. (2021) subscribed that robot human-likeness leads to higher customer evaluation of service encounters and higher service revisit intention. However, Lu et al. (2019) claimed a negative association between robotic anthropomorphism and people’s willingness to use service robots. Moreover, a few studies reported an insignificant effect of anthropomorphism or humanness on user perceptions, for example, trust (Blut et al., 2021; Erebak and Turgut, 2019; Hancock et al., 2011), and acceptance of robotic agents (Fernandes and Oliveira, 2021). Notably, recent studies cartographically depicted a nonlinear relationship between anthropomorphism and user responses (Mathur and Reichling, 2016; Zhang, Meng, et al., 2021). On this, Zhang et al. (2021) found an inverted-U relationship between the perceived humanity of AI virtual robots and users’ trust, which further affects user acceptance of AI virtual robots.

Although a growing body of literature on user responses to robots has emerged in the IS field, most of the literature has investigated users’ responses during or after HRI. Unfortunately, users’ pre-interaction responses are not yet fully understood. This is somewhat surprising because comprehending the pre-interaction responses of service robots is highly important in end-user decision-making on robot adoption and, thereby, on the success of HRI implementation (Duffy, 2003; Fong et al., 1974; Groom and Nass, 2007). In this regard, exploring humans’ perceptions of and reactions to robots at the pre-interaction stage is a promising new research avenue that can provide valuable insights for theorizing robotic research and designing social robots.

2.1.2 Novel Capabilities Challenging Conventional IS Assumptions

The conventional perspective of IS research has considered technology (e.g., Internet banking and decision support systems) as a mere tool for solving problems or providing services for users (Benbasat and Zmud, 2003; Demetis and Lee, 2018; Schuetz and Venkatesh, 2020). Being embodied by such terms as “technological artifacts” and “IT artifacts”, this tool view refers to technologies that are created by humans and used by them to achieve their goals (Lee et al., 2015; Orlikowski and Iacono, 2001; Schuetz and Venkatesh, 2020). From the tool standpoint, users are aware of their unilateral interactions with a technological artifact, and the technological artifact should generate homogeneous outcomes through consistent and transparent functionality and structured inputs irrespective of physical environments (Benbasat and Zmud, 2003; Demetis and Lee, 2018; Schuetz and Venkatesh, 2020). For example, in the basic human–computer interaction model, users interact with IT artifacts via a UI, through which the interaction develops through a user providing some input to the IT artifact, and the IT artifact returns some outputs to the user by combining logical rules and mathematical operations.
However, driven by AI, service robots have entered various domains that formerly were preserved for humans; they possess the ability to adapt their behavior based on inputs from users and their unspecific surroundings. For instance, service robots can interact with humans in more natural ways using speech and gesture recognition; they can also learn from their environment and previous interactions, enabling them to adapt to new situations and provide personalized solutions. This marks a significant departure from the tool view of technology because service robots are now capable of engaging in complex, multi-dimensional interactions with users. In this regard, service robots possess a range of novel capabilities that can revolutionize the way we perceive technology. Based on Schuetz and Venkatesh (2020), I specify five novel capabilities of service robots that challenge conventional assumptions in the IS field.

**Bilateral relationship.** The tool view reflects an IS assumption in user–system interaction that a clear-cut unilateral relationship between an end-user and technological artifact (Akhlaghpour et al., 2013; Schuetz and Venkatesh, 2020). A user inputs specific information/data to a system through a UI, and the system produces outcomes based on predesigned computation. However, service robots break this assumption by being interactive (Chiang et al., 2018; Sheridan, 2016), which means that a service robot not only works as a tool, but also collaborates with a user to complete the assigned tasks and achieve the goal. An example of the bilateral relationship in user–robot collaboration is ChatGPT, which can interact with users and further ask for missing information or narrow down the information scale when it receives insufficient information from users to identify and complete tasks. In this vein, both humans and service robots play the role of the user.

**Environmental awareness.** Conventional IS innovations typically generate outcomes under system–specific circumstances and are isolated from their situated environments (Demetis and Lee, 2018). In contrast, service robots deliver service outcomes by processing unspecific inputs received from their dynamic service environments, in addition to unspecific inputs from users (e.g., natural language) (Demetis and Lee, 2018; Schuetz and Venkatesh, 2020). For example, the social humanoid robot Sophia is equipped with cameras within her eyes, allowing her to capture visual cues in her surroundings and have computer vision algorithms to process acquired visual inputs (Mallonee, 2018). The ability to cope with unstructured data streams is critical for service robots to adapt to changing information and evolving goals/requirements and to respond recursively to interactions (Demetis and Lee, 2018; Schuetz and Venkatesh, 2020). In this regard, service robots can be aware of their surroundings and adapt and react to their environments.

**Functional adaptivity and opacity.** Stemming from the tool perspective, technologies serve as tools that exhibit functional stability (Benbasat and Zmud, 2003; Demetis and Lee, 2018), whereas their functional deficits are primarily because of IT governance weaknesses (Belanche et al., 2020b; Pitt et al., 1999) regarding the misalignment between IT strategy and business strategy (Boritz and Lim, 2008). The consistent functionality held by conventional IS assumptions is oriented by a determined computation protocol (e.g., explicit if-then clauses) (Schuetz and Venkatesh, 2020; Tiwana et al., 2010), hence producing the outcomes of predictability and homogeneity (Paradice and Courtney, 1986).
In contrast, service robots are adaptive and contextual. The adaptive functionality of service robots is derived from sophisticated algorithms of probabilistic computations, thus enabling them to process various unspecified inputs and adjust their responses accordingly (Ferreira et al., 2020; Schuetz and Venkatesh, 2020). In practice, service robots acquire new capabilities by training increasing amounts of data streams and learning from feedback. These new capabilities are driven by tens of thousands of artificial neurons interconnected in service computation–dependent networks, which are generally beyond humans’ comprehension (Ferreira et al., 2020; Schuetz and Venkatesh, 2020). As such, service robots are built on probabilistic (rather than deterministic) computations because the robotic service outcome is singling out the optimal option from the most accurate outcomes by training neural networks (Launchbury, 2016; Schuetz and Venkatesh, 2020). The indeterministic computations lead to functional opacity in AI robots, the so-called “black box”, thereby resulting in unpredictable outcomes (Castelvecchi, 2016; Salem et al., 2013; Schuetz and Venkatesh, 2020).

**Usage unawareness.** Conventional IS research is founded on the assumption that users are aware of the usage of technological artifacts as tools because the user–system interaction is accomplished by inputting information through a specific UI. As proof, the technology acceptance theories were established on individual utilitarian (e.g., perceived usefulness and ease of use) and hedonic (e.g., perceived enjoyment) perceptions of technological features (Davis, 1989; Davis et al., 1992). There is a fundamental assumption that users have deliberation, attitude, and intention toward the technological artifact that they are using. Bearing human-like capabilities, service robots break out of this assumption by virtue of being interactive and iterative. Chatbots can be a good example of showing user unawareness, which is designed to interact with customers by mimicking human-like interactions. They can specify a problem by iteratively acquiring information by asking questions and keeping previous answers in memory. The ability to engage in human-like back-and-forth conversations is demanding for users when it comes to differentiating a chatbot from a human agent if the user has no knowledge of the chatbot’ presence. As a result, the basic IS assumption that users are aware of when they are using technological artifacts may not be applicable in the context of service robots.

These new capabilities of service robots challenge several conventional IS assumptions (Benbya et al., 2021; Schuetz and Venkatesh, 2020), implying that end-users may respond differently to service robots than conventional technological artifacts. This yields the necessity to investigate consumer responses to service robots based on these new assumptions, which also motivates the present dissertation. Figure 2 illustrates the new capabilities of service robots that disrupt conventional IS assumptions.
2.2 Consumer Response to Service Robots/Robotic Service

With the influx of robotics into the service sector in recent years, consumer responses to service robots/robotic service have gradually become a central theme of robot research in IS. Appendix B presents a breakdown of the literature on consumer responses to service robots/robotic agents. Summarizing the literature, studies have primarily utilized technology adoption-related, service experience-related, or HRI theories to explain individual perceptions and reactions.

2.2.1 Robotics Adoption View

From the standpoint of technology adoption, the first research stream of robot research has mainly applied the technology acceptance model (TAM) and its components or extended theories to investigate the antecedents of intention to use robots. Although the service robot has several new characteristics distinct from conventional IS agents, its fundamental essence as technological innovation makes the applicability of TAM valid in predicting the usage intention of service robots. In particular, the two specific utilitarian variables from the initial TAM (Davis, 1989)—namely perceived usefulness and ease of use—together with the hedonic variable, that is, perceived enjoyment (Davis et al., 1992), have been underlined as the fundamental determinants of user acceptance (Abou-Shouk et al., 2021; Ghazali et al., 2020; Li and Wang, 2022; Pitardi and Marriott, 2021). In addition, several core constructs from the unified theory of acceptance and use of technology (UTAUT), including performance expectancy, effort expectancy, social influence, and facilitating conditions, have also attracted enormous attention in robot adoption studies (Amelia et al., 2022; Lee, Lee, et al., 2021; Zhang, Gursoy, et al., 2021). TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003), inclusive of self-service technology theory (Meuter et al., 2005), form the theoretical groundings for many studies in devising sophisticated conceptual frameworks, such as the service robot acceptance model (sRAM) (Wirtz et al., 2018), the service robot integration willingness scale (Lu et al., 2019), the interactive technology acceptance model (Go et al., 2020), the AI device use acceptance model (Gursoy et al., 2019), and the hotel-specific service robot acceptance model (Fuentes-Moraleda et al., 2020).

Apart from the core determinants derived from TAM and UTAUT, many studies have focused on differences between conventional technological artifacts and service robots to account for the distinct nature of robotics adoption. For example, in addition to two variables...
(performance efficacy and facilitating conditions) drawing on UTAUT, Lu et al. (2019) also included anthropomorphism as a negative antecedent, as well as intrinsic motivation and emotions as positive antecedents, to predict consumers’ willingness to use service robots. Based on the sRAM of Wirtz et al. (2018), Fernandes and Oliveira (2021) ascertained a multidimensional acceptance framework of digital voice assistants, including functional components (perceived ease of use, perceived usefulness, and subjective social norms), relational components (trust and rapport), and social components (perceived humanness, perceived social interactivity, and perceived social presence). Likewise, Lee et al. (2021) established an acceptance model of robot assistants in hotel settings by integrating functional aspects (performance expectancy, facilitating conditions, and perceived importance) and emotional aspects (innovativeness, social presence, and hedonic motivation). The study by Park and Kwon (2016) elaborated on the significance of perceived enjoyment and service quality in determining perceived utilitarian value (perceived usefulness and ease of use), affecting attitudes and intention to use teaching assistant robots. To summarize, the literature on the robotics adoption view has primarily been based on technology acceptance theories, incorporating the antecedents from robotic features, for example, anthropomorphism (Fuentes-Moraleda et al., 2022; Li and Wang, 2022) and intelligence (Amelia et al., 2022; Chuah et al., 2021); end-user characteristics, for example, personal innovativeness (Lee, Sheehan, et al., 2021; Lin et al., 2021) and technological anxiety (Blut et al., 2021; Lee, Sheehan, et al., 2021); and relational elements, for example, trust (Fernandes and Oliveira, 2021; Liu, He, et al., 2022; Seo and Lee, 2021) and rapport (Blut et al., 2021; Fernandes and Oliveira, 2021).

### 2.2.1 R-Service Experience View

The second research stream focuses on consumers’ r-service experiences and utilizes service-related theories as the critical theoretical lens. The most intuitive conceptualization of r-service is deploying service robots to assist or replace human personnel to offer consumer service. In this vein, a robot end-user takes the role of a consumer of r-services, who undoubtedly cares for the received service quality service experience. The acclaimed SERVQUAL, originating from human-delivered services, has been extended to the r-service quality evaluation (e.g., Chiang and Trimi, 2020; Kim and Lee, 2014). SERVQUAL consists of five subdimensions to measure service quality: tangibility, responsiveness, reliability, empathy, and assurance (Parasuraman et al., 1988). Morita et al. (2020) extended SERVQUAL by consolidating interactivity and entertainment and identifying the significance of assurance, responsiveness, and entertainment factors in improving customer satisfaction with r-services in the café context. By integrating SERVQUAL and TAM, Meyer-Waarden et al. (2020) confirmed the significance of tangibles and reliability in facilitating the continuous use of chatbots and the role of credibility in triggering customer trust. Furthermore, a body of the literature has focused on understanding how consumers perceive r-service quality in terms of the human embodiment of service robots (Milman et al., 2020; Yoganathan et al., 2021), interaction quality (Choi et al., 2020; Kim et al., 2016; Tuomi et al., 2021), outcome quality (Chi et al., 2021; Choi et al., 2020), and human-centeredness aspects (de Kervenoael et al., 2020; Moussawi and Koufaris, 2019).
Service failure and recovery have attracted the attention of r-service researchers. Several studies have endorsed that the physical presence of service robots affects consumer responses to service failures. Specifically, Fan et al. (2020) concluded that consumers have expressed differentiated degrees of dissatisfaction with service failures resulting from anthropomorphic (vs. nonanthropomorphic) self-service machines, here contingent on consumers’ interdependent self-construal and technological self-efficacy. Analogously, Choi et al. (2021) shown that consumers were even more dissatisfied with the lack of warmth after a humanoid (vs. nonhumanoid) AI agent caused a process failure, while humans can salvage service failures with a sincere apology and restore warm perceptions. Lv et al. (2021) demonstrated the positive effect of the cuteness design of service robots on customer tolerance of service failures. Lv et al. (2022) found that a high-empathy AI response in service recovery can foster continuous usage intention, whereas interaction modality (text only vs. text and voice) moderates the relationship between AI empathic response and psychological distance. Mozafari et al. (2021) employed attribution theory to understand user responses to different r-service experiences under different robot-design strategies; they concluded that users tend to claim responsibility for service successes but are prone to blame service failures on external circumstances.

2.2.3 Human–Robot Interaction View

Another research stream in robot research is to understand user responses to service robots/r-services by applying theories from an HRI perspective. Based on this standpoint, consumers may assess the attractiveness of r-service outcomes differently. A large number of previous studies have discussed consumer responses to r-services from the viewpoint of multidimensional values: expectation for service success, such as performance expectancy (Chuah et al., 2021; Fuentes-Moraleda et al., 2022); attainment value, such as perceived importance (Lee, Lee, et al., 2021; Tussyadiah and Parkb, 2018); intrinsic value, such as intrinsic motivation (Lu et al., 2019; Tuomi et al., 2021) and hedonic perceptions (Abou-Shouk et al., 2021; Pitardi and Marriott, 2021); utility value, such as extrinsic drivers (Tuomi et al., 2021); cost value, such as effort expectancy (Amelia et al., 2022; Zhang, Gursoy, et al., 2021) and privacy invasion (Jain et al., 2022; Park et al., 2021).

Notably, UVH has been extensively used as a theoretical tent, along with other theories, to comprehend user responses to service robots by exploring the influence of robotic anthropomorphism (e.g., Fernandes and Oliveira, 2021; Huang et al., 2021; Odekerken-Schröder et al., 2022; Romero and Lado, 2021). Drawing upon UVH, a handful of studies have incorporated anthropomorphism as an important antecedent affecting the (re-)patronage of consumer r-service through the mediators of perceived utilitarian and hedonic values (Fuentes-Moraleda et al., 2022; Li and Wang, 2022). In addition, numerous other variables affected by anthropomorphism have also been discussed, including perceived threat (Huang et al., 2021; Kim et al., 2021; Yogeeswaran et al., 2016), trust (Mathur and Reichling, 2016; Qiu and Benbasat, 2009; Seymour et al., 2021), and likeability (Amelia et al., 2022; Blut et al., 2021; Salem et al., 2013), to name but only a few.
3. Synthesizing Summary of the Papers

The present dissertation consists of four distinct but interrelated research papers that analyze consumer responses to service robots from the pre-interaction to post-interaction stages. Although each paper varied in its specifics, they shared common elements. With the exception of the literature review papers, the studies followed a positivist paradigm and employed a quantitative methodology with a deductive approach. These approaches were informed by theories that have been widely used in service science and IS research to explain end-user responses and behaviors. Additionally, all the papers were empirical and examined consumer responses to service robots.

This chapter provides a summary of the four papers included in my dissertation, outlining how they fit into the conceptual framework (Figure 1) presented in Chapter 1. Each subsection provides details on the research design, including objectives, theoretical foundations, level of analysis, analytical methodology, and findings. This chapter demonstrates the localization described in Chapter 2: Paper 1 focused on the antecedents and effects of pre-interaction perceptions of robots, specifically comfort with robots. Paper 2 established a comprehensive framework for consumer acceptance of service robots, while Paper 3 introduced an r-service quality evaluation index based on a systematic literature review. Finally, Paper 4 examined the impact of service heterogeneity on consumer post-interaction responses to service robots by drawing from the perspective of functional adaptivity. Each paper represented a distinct study with a unique research background, utilizing various theories and research methods depending on the corresponding research questions. The following subsections briefly summarize each paper, providing an overview of the data and methods used, as well as the main findings.

3.1 Pre-interaction View

Paper 1: Understanding Pre-interaction Responses to Humanoid Robots: A View of Comfort with Robots

Although a growing body of studies has investigated end-user responses to robotic agents, the current understanding of this topic has largely been based on post-interaction reactions to robots from technology-oriented and service-oriented views. This leaves the sophistication of the pre-interaction process to be elucidated. Given the lack of knowledge about consumer responses to service robots prior to interactional behaviors, Paper 1 aimed to clarify how perceived comfort with robots, here as a comprehensive pre-interaction perception triggered by robotic anthropomorphism, permeates consumers’ implicit social decision-making and influences their adoption decision.

**Theoretical foundation.** UVH and comfort theory were used as the theoretical grounding. UVH (Mori, 1970) assumes a nonlinear relationship between the level of human-likeness of a robot and observers’ emotional reactions to the robot, as illustrated in Figure 3. Concretely, when a humanoid robot bears an imperfect resemblance to humans, it can easily evoke uncanny feelings, eeriness, or even revulsion.
Originating in nursing, comfort theory states that comfort is a comprehensive concept determined by a combination of physical and psychological elements (Ayachi et al., 2015). Comfort entails several meanings and connotations that go far beyond ease or alleviating discomfort (Juhas-Davis, 2015). Overall comfort comprises multidimensions, including physical, sociocultural, psychospiritual, and environmental needs (Wilson and Kolcaba, 2004). On the standpoint of human–environment relation, comfort refers to a harmonious state between human beings and their surroundings in relation to the physiological, psychological, and physical dimensions (Slater, 1985). Bearing this in mind, comfort with robots can be viewed as a state of harmony between a subject and a robot that is observed by or interacted with the subject. The role of customer comfort with service providers in improving service quality has been well articulated in the retail service (Ardelet et al., 2022; Meyer et al., 2017; Spake et al., 2003). Unfortunately, the role of consumer comfort with robots in r-service relationships remains virtually unexplored in the IS domain. It would be informative to elucidate how the physical presence of robots affects the comfort level of observers and how humans respond to robots, such as trust establishment and adoption decisions, particularly in the pre-interaction phase. Accordingly, a research model was established, as shown in Figure 4.

**Figure 3. UVH, adapted from Mori (1970)**

**Figure 4. Research model, Paper 1**

**Data collection.** A scenario-based online experiment was conducted to obtain the empirical data. After obtaining the consent of the participants, one robot image out of a self-created image
sample pool comprising 80 real-world robot images was randomly assigned to each participant. In going over the assigned robot image, the participants were required to fill out a questionnaire accordingly. The participants were recruited from October 2021 to May 2022 through Amazon Mechanical Turk (AMTurk), a widely used crowdsourcing platform where workers perform the required tasks online in exchange for payment. After filtering inattentive records, 3,893 valid records remained; each of the 80 images received at least 44 responses, with an average of 48.7 responses.

**Methods.** The present study created the measurement items for comfort with robots, following the instrument development procedure prescribed by Moore and Benbasat (1991). Specifically, two different measures of comfort with robots were developed: formative comfort with robots consisting of psychological and physiological comfort (7 and 8 items, respectively), and holistic comfort with robots (6 items) representing the overall comfort level with a robot.

In addition to performing the analysis in R, the structural equation modeling (SEM) technique via SmartPLS 3.0 was mainly used to test the research model. Specifically, the measurement model was first assessed by examining the reliability and validity of all constructs. The structural model was then verified by testing the effect pathways of the proposed hypotheses, together with their significance levels.

**Findings.** Through a large-scale scenario-based experiment, the study validated that sufficient perceived comfort with a robot in the pre-interaction phase plays an important role in users’ willingness to engage in HRI. The study allocated a fine-grained spectrum of anthropomorphism and cartographically delineated the curvilinear effect of anthropomorphism degree on the perceived comfort of robots and human–robot trust. Specifically, the study confirmed a UV-resemblance curvilinear relationship between anthropomorphism and comfort with robots, as well as the relationship between anthropomorphism and trust. Although it presented some features central to the UV conceptualization by Mori (1970), it did not perfectly match the depiction of UV. In addition, this study reveals the mediator role of human–robot trust in the relationship between comfort with robots and usage intention with empirical evidence. The findings offer tools for future research to understand pre-interaction responses derived from social-psychological aspects that can better inform the design of socially competent robots.


Although studies on the drivers of and obstacles to customer adoption of service robots have remained fragmented, this paper built a conceptual framework to comprehend the present knowledge based on a content analysis of the literature to gain insights into customer attitudes and intentions to (re)use service robots. Drawing on a triangulation of perspectives on end-users in adoption research, the framework employed technology acceptance theories, SERVQUAL, and expectancy-value theory to construct the skeleton. In addition, the antecedents influencing customer acceptance of service robots were subdivided into robot-design, consumer-oriented, and relational components, as well as exogenous factors. The paper not only sheds light on the current
state of service robot acceptance research, but also facilitated it by developing a comprehensive framework regarding the effect factors.

**Theoretical foundation.** *Triangulation perspective in adoption research.* Researchers are encouraged to scrutinize a triangulation of three perspectives on end-users in adoption research: technology user, consumer, and network member (Pedersen *et al.*, 2002). Given the triple roles that individuals play in technology adoption, the triangulation view has been widely used in various research fields, such as m-learning (Liu *et al.*, 2010) and m-commerce (Pedersen *et al.*, 2002). Consolidation of theories in terms of the three distinct roles played by the end-user is also called for (AlHinai *et al.*, 2007). For service robots, which are essentially novel technological innovations equipped with AI, r-service customers are undoubtedly the users of robotic technology. As individuals for whom robots deliver service, they naturally play the role of consumers of r-services. It is noteworthy that service robots are deployed as regular service providers to replace human employees in service operations. Different from traditional digital technologies, service robots have a variety of new capabilities, for example, adapting to external environments and imitating human cognitive abilities to initiate more human-like interactions (Schuetz & Venkatesh, 2020), enabling them to respond to service needs by reacting recursively to interactions. As such, a customer who is served by a robot also acts as an interactor who interacts bilaterally with the robot. Therefore, a conceptual framework is structured based on three roles: technology user, consumer, and interactor.

**Data collection.** This paper examined the existing literature focusing on the acceptance and adoption of service robots/r-services. Literature retrieval was performed in Web of Science, Scopus, and the AIS Library. Google Scholar was used as a supplementary source. The topics of interest were empirical studies that understood the acceptance/adoption of service robots, including attitudes toward and intention to (re)use service robots. I carried out inquiries with the following keywords in such possible search fields as title, abstract, and keywords: “robot/robotic service”, “adoption/acceptance/attitude/intention to use/usage intention/willingness to use/behavioral intention/”. Only journal articles and conference papers were selected. Furthermore, I performed an archival retrieval based on the retrieved journal articles to ensure that the literature list was extensive and that no important articles were omitted. After removing duplicates and unqualified articles, a final sample size of 60 articles remained.

**Methods.** A content analysis was conducted on the remaining 60 articles. This paper established a conceptual framework (see Figure 5) based on previous empirical studies on consumer adoption of either novel technology or services. This visualization displayed the fundamental determinants in the reviewed literature from the lenses of TAM, service quality, and expectancy-value theory pertaining to the threefold roles of technology user, consumer, and interactor, respectively. The operationalizations of the included factors in Figure 5, together with their effects on customer attitude toward and intention to use service robots, were consolidated.

**Findings.** Based on a content analysis of the resulting 60 articles, the paper built a comprehensive framework by consolidating the present knowledge of service robot adoption. In
addition to elucidating and promoting the current status quo of robot adoption research, the framework can also be considered a prototype for studying service robot adoption decisions.

This paper claimed that customers act in multiple roles in HRI, and the antecedents affecting customer acceptance of service robots were categorized into four groups: (1) robot-design components, (2) consumer-oriented components, (3) relational components, and (4) exogenous factors. The results have indicated the complexity of factors affecting consumers’ adoption of service robots. Specifically, not only do robot functionalities matter, but social-emotional elements also play an essential part in service robot adoption.

Several robot-design components remain to be investigated. Future research would turn to a design strategy related to the physical presence of service robots to endear robots to customers and generate affective bonds. Given the wide variety of r-services, pairing robot-design features with service tasks deserves more attention to promote the customer adoption of robots.
Figure 5. Conceptual framework of consumer acceptance of service robots, Paper 2
3.3 Service Quality Evaluation View

Paper 3: Instrument Development for R-Service Quality: A Literature Review

To bridge the research gap on the lack of knowledge on the measurement of r-service quality, Paper 3 reviewed the literature on r-service quality, focusing on the potential methodological issues of developing measurement instruments and identifying the dimensionality of r-service quality. This study was the first systematic literature review on r-service quality dimensionality.

**Data collection.** Following the systematic and structured approach of Webster and Watson (2002), I carried out manual keyword searches in January 2021, primarily on three databases, that is, AIS Library, Scopus, and Web of Science. Google Scholar was used as a supplementary source. I searched for journal articles, conference papers, and book chapters related to r-service quality evaluation. Inquiries with the following keywords were performed in all possible search fields (namely title, abstract, keywords, and main text): “service quality/service evaluation/customer satisfaction/customer delight” and “robot/robotic service”. After collecting all retrieval records, dropping duplicates, and filtering unqualified papers, the final sample comprised 55 papers. These studies either concentrated on developing tools for evaluating r-service or aimed at studying how consumers respond to r-service.

![Figure 6. Literature selection, Paper 3](image)

**Methods.** **Systematic Literature Review.** The research model and main findings of the reviewed papers are presented in the systematic literature review. With a content analysis of 55 articles, the study identified 10 dimensional measures regarding r-service quality, including tangibility, responsiveness, reliability, empathy, assurance, ease of use/usability, usefulness, anthropomorphism, perceived intelligence, and social presence. This review showed that the dimensions of r-service quality tended to be contingent on specific contexts of the service industry/type. Several methodological limitations of the literature in developing the measurement scales of r-service quality were identified, providing valuable implications for future studies.
Findings. Existing measures of r-service quality generally involve robot design and service delivery quality, including factors that trigger consumer willingness, satisfaction, and/or (re)use intention. A widely accepted measure of r-service quality is lacking in the literature. Although a consensus in the construct of r-service quality regarding its dimensions has not yet been reached, several dimensions were frequently considered. This study identified ten common dimensions for r-service quality, including SERVQUAL’s five dimensions, ease of use/usability, usefulness, and three robot-related dimensions. In this vein, the study demonstrates that the measurement of r-service quality shares several dimensions with traditional human-delivered service and e-service. Meanwhile, some dimensions of r-service quality are distinctive from conventional service settings. These distinctive dimensions focus on the social-emotional factors primarily induced by robot characteristics.

Moreover, the study outlined the methodology of instrument development for r-service quality by analyzing the methodological issues of the literature in terms of sampling, research context, survey administration, measurement items generation, and dimensionality analysis. Based on this, future studies should make more efforts in the methodological approaches to identifying dimensions by conducting qualitative research and generating measurement items of r-service quality, as well as the sampling methods and size. Random and relatively larger sample sizes across multiple service industries are also recommended.

3.4 Post-Interaction View

Paper 4: Consumer Responses to Robotic Services: A View of Service Heterogeneity

Although conventional digital services are homogenous, standardized, and predictable in terms of system inputs and outputs, r-services deal with unstandardized system inputs from both users (e.g., users initiated verbal dialogue) and/or environments (e.g., different lighting conditions or people moving around), resulting in an unstandardized system response or often unique service output for different users. Nonetheless, there is a lack of knowledge on users’ responses to r-services that are featured with heterogeneity. This study offered a theoretical account distinguishing r-services from conventional digital services and human services from the view of service heterogeneity. Several hypotheses were proposed by taking into account both the characteristics of end-users and the nature of the service, which were tested via two different studies.

Theoretical foundation. Functional adaptivity of service robots. Service robots can adapt their behaviors based on the information they perceive from both users and the situated environment; thus, service robots have been characterized by functional adaptivity compared with the functional consistency of conventional IS (Belanche et al., 2020b; Schuetz and Venkatesh, 2020). The functional adaptivity of service robots stems from two remarkable technical features. First, service robots act (semi)autonomously in a dynamic service environment by processing unspecific inputs. Second, the service computations of service robots are indeterministic as opposed to the deterministic computations in conventional digital services (i.e., logic and rules) (Schuetz and Venkatesh, 2020). The unspecific system inputs and the indeterministic nature of AI-based service computations have contributed to the functional adaptivity in service robots, leading to the
behavioral unpredictability of service robots and variability in r-service outcomes. As a result, the production and outcomes of r-services may vary. Table 1 presents a comparison of both the inputs and computations required for human-delivered services, conventional digital services, and r-services; the two rightmost columns illustrate the homogenous nature of conventional digital services and the nature of being contextual and adaptive in service robots, thus, heterogeneous for r-services.

Table 1. Comparison of human-delivered services, conventional digital services, and r-services

<table>
<thead>
<tr>
<th>Service input</th>
<th>Human-delivered service</th>
<th>Conventional digital service</th>
<th>R-service</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Unspecific</td>
<td>• Specific</td>
<td>• Unspecific</td>
</tr>
<tr>
<td></td>
<td>• Bilateral</td>
<td>• Unilateral</td>
<td>• Bilateral</td>
</tr>
<tr>
<td></td>
<td>• Contextual</td>
<td>• Noncontextual</td>
<td>• Contextual</td>
</tr>
<tr>
<td></td>
<td>• Environment dependent</td>
<td>• Environment-agnostic</td>
<td>• Environment dependent</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Service computation</th>
<th>Human-delivered service</th>
<th>Conventional digital service</th>
<th>R-service</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Human (employee and customer) reasoning is opaque and not always rational.</td>
<td>• The service computation is deterministic.</td>
<td>• The service computation (fueled by AI) remains a “black box.”</td>
</tr>
<tr>
<td></td>
<td>• Functionality can be affected by internal and external factors, such as personality, mood, service skills, and service sites.</td>
<td>• Well-defined algorithms lead to functional consistency.</td>
<td>• Functionality arises from probabilistic complexity functions that are inherently incapable of validating a function through logic.</td>
</tr>
</tbody>
</table>

Through a systematical literature review on service heterogeneity, I identified one primary antecedent, namely previous experience, and three important resultants of perceived service heterogeneity, including perceived risk, service expectation, and service revisit intention. An initial conceptual model was established accordingly. However, recent studies have indicated that consumers respond differently to human employees from robotic agents, as well as in satisfying and dissatisfying service scenarios. To account for these factors, the study incorporated two key manipulations: service providers (robots or humans) and service situations (satisfying or dissatisfying). As a result, the research framework was developed, as illustrated in Figure 7.

H1: Compared to the users with prior r-service experiences, users without r-service experiences will develop a stronger perception of service heterogeneity in r-service.

H2: With prior r-service experience, consumers perceive lower service heterogeneity with r-services than with human-delivered services.

H3: Consumers’ perceived r-service heterogeneity positively affects their perceived risk.

H4: Service heterogeneity has a stronger positive effect on perceived risk for consumers with r-service experience than those without.

H5: Service situation moderates the relationship between r-service heterogeneity and perceived risk.

H6a(b): In a satisfying (dissatisfying) service situation, service heterogeneity has a negative (positive) total effect on customer revisit intention.

Figure 7. Research framework, Paper 4
**Data collection.** A scenario-based experiment (Study I, with $2 \times 2$ service scenarios) and a field study (Study II, with two service situations) were carried out to triangulate the results. Specifically, Study I was based on a single predesigned service scenario—hotel reception service. The responses of both experienced and inexperienced consumers were recorded. As a result, 746 valid samples were obtained for inexperienced consumers and 559 valid responses for experienced consumers.

Study II examined general $r$-services in various real settings and collected field data from actual consumers of $r$-services to avoid the results from suffering from projection biases because of insufficient real-life experience being served by robotics. After screening the inattentive records, 358 valid records were obtained, with 206 and 152 valid samples of satisfying and dissatisfying experiences, respectively.

**Methods.** Two-sample t-tests and the SEM technique were mainly utilized to test the research model, which was done using AMOS 28.0. This software helps facilitate the analysis of the measurement and structural models (Chin et al., 2003). Based on the recommended procedure (Hulland, 2015), all latent variables were first assessed for internal consistency and validity. After they were found to satisfy the parametric requirements of the path test, the structural model was tested.

**Findings.** This study elaborated on the functional adaptivity of service robots, which motivated us to adopt the view of service heterogeneity to study users’ responses to $r$-service. The findings show that prior $r$-service experience played a distinct role in shaping customers’ perceived heterogeneity of $r$-services, with experienced consumers perceiving significantly lower heterogeneity than inexperienced consumers. Moreover, the study highlighted the crucial role of prior $r$-service experiences in affecting users’ perceptions and revisit intentions in the novel context of $r$-services. Specifically, prior $r$-service experience moderated the effect of service heterogeneity on perceived risk.

The study confirmed that the service provider (human or robot) has a significant influence on perceived $r$-service heterogeneity among experienced consumers. This finding affirms the existence of heterogeneity in $r$-services, and its magnitude is perceived as higher than conventional digital services but lower than that of human-delivered services. This finding underscores the relevance of heterogeneity in the $r$-service context for IS research, highlighting service heterogeneity as a valuable angle for understanding consumer responses to $r$-services.

Additionally, the study shows that the impact of service heterogeneity on perceived risk differs between satisfying and dissatisfying service situations. The importance of distinguishing the effect of service heterogeneity in these situations was emphasized because it can magnify or attenuate the effect of heterogeneity on consumer perceptions. Furthermore, the direction of the effect of service heterogeneity on service revisit intention varied across different situations, with service heterogeneity positively (negatively) influencing consumers’ intentions to revisit the service in a dissatisfying (satisfying) service situation.
4. Discussion and Conclusions

The purpose of the present dissertation has been to provide comprehensive insights into consumer responses to service robots through four standalone yet interconnected studies examining consumers’ emotion, cognition, and behavioral intentions occurring from pre-interaction to post-interaction with a service robot. This chapter describes the implications of the dissertation for both academic research and practical applications. In addition, the limitations of the dissertation are acknowledged, and avenues for future research are recommended.

4.1 Implications for Research

By addressing the earlier mentioned five sub-research questions, the dissertation has demonstrated a holistic understanding of how consumers respond to service robots from comfort with robots, robotics adoption, service quality evaluation, and service heterogeneity view. The contributions to robotic research in the IS discipline are sixfold.

First, the dissertation has made a valuable contribution by revisiting conventional IS assumptions of user–system interaction and pointedly identifying novel capabilities of service robots, particularly in light of the emergence of AI-enabled robots challenging conventional IS assumptions. Compared with conventional IS, service robots exhibit multiple novel capabilities, such as being aware of situated environments and functional adaptivity. This results in the inapplicability of conventional IS assumptions in the robotic context. In this vein, the dissertation has shown the necessity of introducing new lenses and developing new theories in the novel context to offer a better understanding of consumer responses to service robots/services. By emphasizing that consumer perceptions of service robots start to shape before HRI, Paper 1 was a pioneering attempt to systematically introduce comfort theory into IS research while offering theoretical explanations for consumers’ pre-interaction perception development in r-service delivery. Furthermore, inspired by Schuetz and Venkatesh (2020), Paper 4 has stood on the novel capability of functional adaptivity in service robots, complementing the traditional IS assumption of functional consistency and verifiable outcomes in conventional digital agents. By innovatively extending the conceptualization of heterogeneity to the r-service context, the present dissertation is among the first to systematically draw into the lens of service heterogeneity in r-service in the IS domain. Paper 4 facilitates a novel theoretical account of the different service outcomes delivered by service robots, which can be applied to better understand consumer post-interaction perceptions of r-services. In this regard, the dissertation has contributed to a more nuanced understanding of the role of robotics in shaping the future of IS research by shedding light on the unique features and capabilities of service robots. This dissertation will serve as a catalyst for further research in the IS field and inspire new avenues for exploration and innovation.

Second, echoing the recent call for more IS research on AI-based agents and AI-enabled services (Benbya et al., 2021; Diederich et al., 2022), the current dissertation has enriched the current literature by rendering a holistic understanding of consumer responses to service robots with a broad spectrum from pre-interaction to post-interaction with robots. Specifically, (1) Paper 1 added consumer pre-interaction responses to the literature, which previous studies have omitted. This
study contributed new knowledge for robotic research in IS by illuminating how comfort with robots is induced and how it penetrates consumers’ implicit social decision-making (human-robot trust). (2) By better comprehending the existing robotics adoption literature, Paper 2 consolidated the present knowledge on service robot acceptance by establishing a comprehensive framework for a detailed understanding of the antecedents determining consumer attitudes and intention to use service robots. This study advanced the current discussion by taking the triangulation of three roles that end-users of service robots are involved in, including the technology user, r-service consumer, and interactor. (3) By systematically reviewing the literature on r-service quality assessment, Paper 3 complemented the current r-service literature by identifying the dimensionality of r-service quality and proffering insightful methodological implications for developing measurement scales of r-service quality. (4) From a post-interaction view, Paper 4 provide a theoretical account from the view of heterogeneity that establishes a solid basis for studying consumer responses to service robots, which can be further extended to understand r-service from different aspects (e.g., trust). To sum up, the present dissertation has added valuable insights to the literature on consumer response to service robots penetrating the overarching phases: pre-interaction emotional arousal → robotics adoption → r-service quality evaluation → post-interaction responses. This helps lay the groundwork for comprehending the full story of consumer response to service robots.

Third, the present dissertation has also broadened the scope of previous studies by demonstrating the sophisticated underlying mechanisms of how consumers respond to service robots at different stages, specifically the primary appraisal and outcome phases. The findings in Paper 1 have highlighted the role of sufficient perceived comfort with robots in consumers in initialing human–robot trust and fostering their willingness to engage in HRI. Although past studies have focused on consumer responses during or after HRI, the dissertation has contributed to untangling the underlying mechanism of how comfort with robots induced by robotic anthropomorphism affects consumer adoption decisions of service robots through the mediator of human–robot trust. In addition, Paper 4 identified the antecedents of r-service heterogeneity and delineated the effects of prior r-service experiences and service providers on service heterogeneity. Meanwhile, Paper 4 also unmasked the impacts of perceived heterogeneity in r-services on consumer perceptions and re-patronage under different boundary conditions, including (with/without) prior r-service experience and (satisfying vs. dissatisfying) service situations. This clarified finding highlights the need to better understand consumer responses to service robots after a service failure, echoing the works of Merkle (2019) and Stock (2018). Thus, the variations in the responses to service heterogeneity in the two different situations thus offer new knowledge that complements the literature on service heterogeneity. In this instance, Paper 4 has been conducive to filling up the current research void on consumer responses to r-service heterogeneity by clarifying the boundary condition concerning the consumer characteristic of previous experience deductively. This is critical for advancing IS robotic research on the related theories of r-service and the lens of functional adaptivity.

Fourth, the present dissertation has shed light on the implications of configuring consumer characteristics, features of service robots, and other contextual factors to fostering consumer
behavioral intention in future research. Paper 1 determined the role of robotic anthropomorphism in affecting consumer pre-interaction perceptions. Paper 4 highlighted the importance of consumer characteristics in terms of prior r-service experience and their assessment of prior experience (i.e., satisfying or dissatisfying service situations) in influencing post-interaction responses. Thus, the dissertation has responded to recent IS research advocating for exploring the role of robot-design features and end-user characteristics in shaping user perceptions of AI robotic agents and interaction outcomes across different contexts (Blut et al., 2021; Diederich et al., 2022). Alongside the most presented robot-design components described in my dissertation, further investigation is desired on robot-design strategies, such as cuteness design, to endear robots to customers and generate affective bonds. In addition, how to pair robot-design features with service tasks deserves more attention to promote consumer adoption and service assessment, as proposed in Paper 2 and Paper 3, respectively. Likewise, the deliverables from the views of robotics adoption in Paper 2, r-service quality evaluation in Paper 3, and re-patronage decision-making in Paper 4 have all placed emphasis on multidimensional components covering the embodiment/functionalities of robots, end-user characteristics, and social-emotional elements. In other words, the dissertation has indicated the potential of configuring these aspects in future IS robotic research.

Fifth, the dissertation is conducive to understanding the existing fragmented knowledge of robotics adoption and filling the void of instrument development for r-service quality, here by virtue of the deliverables of Paper 2 and Paper 3, respectively. On the one hand, the proposed robot acceptance framework in Paper 2 and the dimensionality of r-service quality in Paper 3 can be considered a prototype in robotic research and extended to future studies by empirically investigating the weights of different factors/dimensions to further determine the most significant factors. On the other hand, by indicating variations of the determinants in fostering robot adoption in Paper 2 and r-service quality in Paper 3 because of situational differences, this dissertation offers a knowledgeable basis for future research to build service industry/type-specific service acceptance frameworks and r-service quality indexes, further validating them with empirical evidence.

The final contribution of the present dissertation lies in instrument development and verification. Previous studies have virtually not discussed pre-interaction perceptions regarding comfort with robots, despite the fact that a few exceptions can be found peripherally touching on the importance of users’ comfort with robots (Duffy, 2003; Fong et al., 1974; Groom and Nass, 2007). In addition, although heterogeneity has aroused extensive discussion in service literature, it has attributed little attention to measurement development. Little is known about the r-service heterogeneity resulting from the capability of the functional adaptivity of service robots, as well as its effect on consumer responses. Following the systematic instrument development procedure prescribed by Moore and Benbasat (1991) and Sun (2012), the current dissertation has developed and verified two kinds of measurements for comfort with robots in Paper 1, that is, holistic comfort and formative comfort comprising psychological comfort and physiological comfort, and the measurement items for service heterogeneity in Paper 4. The proposed measure instruments can be utilized to determine the perceived valence and magnitude of comfort with robots and service
heterogeneity, respectively, in future empirical studies and to facilitate future studies on service robots/\textit{r}-service.

4.2 Implications for Practice

The practical implications of the findings can be viewed from four different angles with respect to incorporating robotics into the daily operations of service industries.

First, the present dissertation provides recommendations for robotic design and optimization to promote favorable customer responses toward service robots. The empirical investigation in Paper 1 demonstrated that the formation of consumer perceptions is initiated from the pre-interaction stage by primarily observing the physical appearance of service robots. Paper 1 presented compelling evidence regarding the impact of UVE on HRI. Specifically, it highlighted the role of robotic anthropomorphism in shaping consumers’ perceived comfort with robots and human–robot trust. The findings of Paper 1 suggest that instead of excessively pursuing anthropomorphic designs, robotic designers should aim to avoid the “UV” by intentionally focusing on nonhuman designs that fall in the phase before the first peak. These designs strike a balance between moderate levels of anthropomorphism and considerable comfort and trust with robots, as opposed to the discomfort reactions associated with increasing anthropomorphism to reach the second peak. Alternatively, Paper 1 recommended that designers explore other existential attributes, such as cuteness design, to provoke comfort feelings in observers. All four papers showed the importance of considering the emotional impact of robots as social entities in designing them for service transactions. Consumer perceptions and attitudes towards robots have been largely influenced by their psychological evaluation, and social-emotional elements should be incorporated into the design process to ensure that the robots evoke positive emotions in consumers. In addition to robot appearance, the significance of functional components, particularly ease of use, has been emphasized in the context of robotics adoption in Paper 2 and \textit{r}-service quality assessment in Paper 3. As a result, robot manufacturers should prioritize the functional design of robots to ensure that they are user-friendly and easy to navigate. By doing so, manufacturers can enhance the overall quality of their products and make them more appealing to potential customers, ultimately increasing the likelihood of successful adoption and utilization.

Second, the present dissertation presents valuable insights for service practitioners in terms of service robot deployment in their business operations. As acknowledged by previous studies, the deployment of service robots offers significant opportunities not only to liberate intensive labor reliance (Acemoglu and Restrepo, 2020) but also to improve management efficiency and service delivery performance (Gursoy \textit{et al.}, 2019; Lee, Kwag, \textit{et al.}, 2020; West \textit{et al.}, 2018). However, above all, the success of robotic deployment highly depends on the comfort level of end-users with the technology. The deliverable of Paper 1 indicates that, to ensure customer comfort and enhance the customer experience, \textit{r}-service operators need to be aware of the importance of deploying robots that end-users are comfortable interacting with. With this understanding, operators can develop effective strategies to improve the customer experience accordingly. Furthermore, based on the findings regarding the mediator role of human–robot trust between anthropomorphism and usage intention in Paper 1, service providers are encouraged to
issue strategies that raise and protect the trustworthiness of service robots, particularly from a social-psychological perspective in the pre-interaction stage. This is because trust-building interventions, such as privacy protection and risk reduction are critical in fostering customer engagement in trust-related robot-using behavior.

Furthermore, service managers need to understand the keys to the effective deployment of service robots. Based on this, the implications from Paper 3 convey the importance of ensuring that the delivery of the promised services occurs in a reliable, accurate, and timely manner. In addition, operators are encouraged to provide equipment and interacting skills that are specific to the service being provided. Other essential elements include actively solving customer problems, providing prompt service, performing reliable services consistently and politely, and giving caring and individualized attention to customers. As a result, service practitioners are requested to understand the benefits and obstacles of deploying service robots and to take the necessary steps to ensure successful implementation. This can lead to an enhanced customer experience and improved service delivery performance.

Third, Paper 4 provided suggestions for managing consumers’ risk perceptions of $r$-services, which can be particularly high for first-time consumers. There are several strategies that service managers and practitioners of $r$-services can employ to mitigate customers’ risk perceptions and promote positive experiences. I showed that customers’ perception of $r$-service regarding heterogeneity can increase their perceived risk, particularly for first-time users. $R$-service providers must ensure that customers have a positive initial experience with $r$-services to encourage repeat usage. To achieve this, service managers should provide adequate support during the initial implementation of $r$-services, such as training and troubleshooting, to ensure customer satisfaction. Additionally, practitioners of $r$-services should consider employing preventive measures to address negative post-assessment perceptions, such as designing socially competent robots that can alleviate customers’ negative emotions, particularly when malfunctions occur. Moreover, $r$-service practitioners should tailor their marketing appeals based on customers’ previous experience with robots. Because the novelty of robotic technology can create a sense of unfamiliarity for first-time users, service providers should segment inexperienced customers and develop practical approaches to consumer management that address this unfamiliarity. In doing so, the practitioners of $r$-services can promote positive experiences, reduce customers’ perceived risk, and encourage repeat visits.

Fourth, Paper 4 also contributed to service failure recovery by offering valuable suggestions regarding remedial actions for service failures in $r$-service, which are becoming increasingly prevalent. Despite the inevitability of service failure, it is imperative to consider recovery actions to ensure customer satisfaction and retention. The findings showed that the differences in the responses to $r$-services depended on whether the service experience was satisfying or not. Destination managers of the $r$-service should proactively plan for scenarios where the robot fails to provide a satisfactory service. For instance, automated call systems that allow customers to request assistance from human employees may be necessary for situations where interaction difficulties arise, such as when customers require human intervention or encounter difficulty
communicating with or understanding the dialogue of service robots. Furthermore, follow-up interactions with dissatisfied consumers could provide a valuable opportunity for _r_ -service managers to explain the reasons for service failures, thus mitigating any negative perceptions caused by service failures. Because service robots still lack the capabilities and flexibility to identify and solve service problems completely like humans, _r_ -service managers must explore the underlying reasons for service failures and implement effective solutions to avoid hindering customer reuse. By implementing these suggestions, _r_ -service managers can improve customer satisfaction, retention, and overall service quality, which can have a significant positive impact on the long-term success of _r_ -services.

4.3 Limitations and Avenues for Future Research

Although a comprehensive investigation and analysis were conducted, I realize that the dissertation is not without limitations, which can provide directions and opportunities for future research.

First, although the present dissertation set up a conceptual framework covering numerous constructs that foster service robot acceptance in Paper 2 and identified the dimensionality of _r_ -service quality in Paper 3 from the literature analysis, empirical verification of these deliverables either qualitatively or quantitatively would be fruitful in future research. In addition, the insights gained from Paper 2 and Paper 3 have indicated variations in the factors affecting robot acceptance and _r_ -service quality evaluation from specific service industries and service types. Therefore, paring service contexts, such as service tasks and service types, with the robotics adoption framework and _r_ -service quality index also deserve more attention in future research. In addition, despite the confidence of the proposed conceptual framework in proffering a coherent overview of most factors of high relevance under the robotics adoption context in Paper 2, not all factors affecting consumer attitudes and usage intentions of service robots or other robotic agents have been enveloped in the current literature or addressed by other work.

Second, future research can take robot motion, robot types, and service contexts into account when investigating end-user responses to service robots. Whereas the present dissertation was based on observing real-world robot face images when examining consumers’ pre-interaction responses in Paper 1, more interesting findings may be achieved by using robotic entities as stimuli in experimental or dynamic service settings and considering robot movement. This can allow for more worthwhile research and managerial insights to burgeon in the robotic research of the IS realm. Paper 4 was conducted based on a scenario-based online experiment that manipulated service situations and service providers and a field study based on consumers’ self-recalled memory. Prospective studies in real-life contexts across different service settings and service robot types are recommended as supplements.

Third, I call for more research to investigate the influence of end-user characteristics in HRI on their perceptions of and responses to service robots. The present dissertation has placed emphasis on consumers-oriented components, such as personal innovativeness and previous experience, in robotics adoption (Paper 2), as well as previous _r_ -service experience in post-interaction responses to service robots (Paper 4). Future studies should demonstrate the
generalizability of related findings by considering r-service consumers with different cultural backgrounds and social dimensions. This echoes that similar findings observed across diverse populations and research settings can improve the evidence supporting external validity. Moreover, the insights obtained from Paper 4 have indicated gender differences in responses to r-services. Although the effect of end-user gender on their acceptance of robots has been well-articulated in previous studies (e.g., McCartney and McCartney, 2020), further work is recommended to clarify how gender affects consumer responses to r-services and matching different service robots and consumer characteristics, such as gender, across service settings.

Fourth, although limited constructs have been considered, future studies are encouraged to examine more related aspects of service robots and consumer responses. Unlike conventional IS innovations, service robots exhibit many unprecedented new features that may affect consumer perceptions and reactions before and after r-service delivery, which deserves further investigation. Concretely, Paper 1 delineated the influence of robot anthropomorphism on observers’ perceived comfort with robots. However, there might be several predictors of robot attributes in terms of physical presence that may affect perceived comfort with robots, such as cuteness and aesthetics. In this vein, it would be promising to investigate more precedents that provoke end-user comfort and/or discomfort with robots in future studies, as well as other pre-interaction perceptions and reactions. Analogously, Paper 4 focused on two kinds of perceptions directly resulting from service heterogeneity: perceived risk and service expectations. A more comprehensive study that addresses other factors, such as trust, is warranted.

References


### Appendix A. Empirical Literature on Users’ Responses to Characteristics of Service Robots

<table>
<thead>
<tr>
<th>Study</th>
<th>Theoretical basis</th>
<th>Robot characteristic orientated factors</th>
<th>Service context</th>
<th>Resultant</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi et al. (2022)</td>
<td>—</td>
<td>Anthropomorphism; Hedonic motivation; Perceived social influence</td>
<td>Airline/hospitality</td>
<td>Willingness to use AI devices; Objection to using AI devices</td>
<td>• Social influence, hedonic motivation, anthropomorphism, performance/effort expectancy, and emotions influence tourists’ acceptance of AI devices. • Social influence is a stronger determinant in hospitality than airline services. • Tourists have higher performance expectancy from AI devices for offering airline services than hospitality. • Willingness to accept AI devices for delivering hospitality services is lower than for airline services. • It is acceptable to use AI devices to provide functional services, but it may be counterproductive to use AI devices to provide hedonic services.</td>
</tr>
<tr>
<td>Liu et al. (2022)</td>
<td>—</td>
<td>Perception of Robot appearance (warm vs. competent)</td>
<td>Hospitality/tourism</td>
<td>Intention to use</td>
<td>• Customers have more willingness to use a service robot perceived as warm in hedonic service contexts and, conversely, competent in utilitarian service contexts. • Trust mediates the influence of the interaction of robot appearance (warm or competent) and service context (hedonic-/utilitarian-dominant) on intention to use.</td>
</tr>
<tr>
<td>Lv et al. (2022)</td>
<td>CDI</td>
<td>AI cuteness (high vs. low)</td>
<td>Tourism, hotel, museum, restaurant</td>
<td>Willingness to use</td>
<td>• Customers have more willingness to adopt AI applications with high cuteness to perform emotional tasks, and the relationship is mediated by social distance. • Customers preferred AI applications with low cuteness to perform knowledge-based tasks, and the relationship is mediated by performance expectancy.</td>
</tr>
<tr>
<td>Lv et al. (2022)</td>
<td>SKI</td>
<td>Empathic response (High vs. Low)</td>
<td>Hospitality</td>
<td>Continuous Usage Intention</td>
<td>• High-empathy AI response increases continuous usage intention in service recovery. • Psychological distance and trust sequentially mediate the influence of (high or low) empathic response on continuous usage intention. • Interaction modality (text-only vs. text and voice) moderates the effect of AI empathic response on psychological distance in AI service failure.</td>
</tr>
<tr>
<td>Odekerken-Schröder et al. (2022)</td>
<td>UVT, MET</td>
<td>Anthropomorphism</td>
<td>Restaurant service</td>
<td>Customer repatronage</td>
<td>• Robot anthropomorphism is positively associated with social presence. • Robot anthropomorphism has a stronger positive effect on utilitarian than hedonic value. • Robots’ social presence is positively associated with customer repatronage intentions. • The quality of frontline employee interactions augments the effect of robots’ utilitarian value on customer repatronage intentions.</td>
</tr>
<tr>
<td>Blut et al. (2021)</td>
<td>UVT, SPT, TIFT</td>
<td>Robot design; Anthropomorphism</td>
<td>Multiple services</td>
<td>Intention to use</td>
<td>• Customer traits and predispositions (e.g., computer anxiety), sociodemographics (e.g., gender), and robot design features (e.g., physical, nonphysical) are triggers of anthropomorphism. • Robot characteristics (e.g., intelligence) and functional characteristics (e.g., usefulness) are important mediators, while relational characteristics (e.g., rapport) receive less support as mediators. • The impact of anthropomorphism on usage intention depends on contextual circumstances, such as the type of robot (e.g., male or female) and the type of service provided (e.g., possession-processing or mental stimulus processing).</td>
</tr>
<tr>
<td>Choi et al. (2021)</td>
<td>SET, MSET</td>
<td>Service robot (Humanoid vs. non-humanoid)</td>
<td>Restaurant service</td>
<td>Satisfaction; Behavioral intention</td>
<td>• Consumers are more dissatisfied due to a lack of warmth following a process failure caused by a humanoid (vs. nonhumanoid). • Humanoids (instead of nonhumanoids) can recover from a service failure by themselves via sincere apology, restoring perceptions of warmth, and effectively providing explanations as a recovery tactic. • Human intervention can mitigate dissatisfaction following inadequate recovery by nonhumanoid robots.</td>
</tr>
<tr>
<td>Study</td>
<td>Theoretical basis</td>
<td>Robot characteristic oriented factors</td>
<td>Service context</td>
<td>Resultant</td>
<td>Main findings</td>
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</tr>
<tr>
<td>Chuah et al. (2021)</td>
<td>CT</td>
<td>Anthropomorphism; Perceived intelligence</td>
<td>General service</td>
<td>Behavioral intention to use service robots</td>
<td>• Multiple, distinct, and equally effective combinations of human-like, technology-like, and consumer features exist to achieve high intention to use service robots.</td>
</tr>
<tr>
<td>Fernandes and Oliveira (2021)</td>
<td>UVT, UTAUT, RT</td>
<td>Perceived humanness; Perceived social interactivity; Perceived social presence</td>
<td>General service</td>
<td>Acceptance of Digital voice assistants</td>
<td>• Functional, social and relational elements drive adoption, and the moderating role of experience and need for human interaction have been identified.</td>
</tr>
<tr>
<td>Huang et al. (2021)</td>
<td>UVT</td>
<td>Anthropomorphic appearance of robots</td>
<td>General service</td>
<td>Usage intention</td>
<td>• Users’ negative attitudes toward more anthropomorphic robots had a stronger negative effect on their usage intention than less anthropomorphic robots.</td>
</tr>
<tr>
<td>Li and Wang (2022)</td>
<td>TAM</td>
<td>Anthropomorphism; autonomy</td>
<td>General service</td>
<td>Behavioral intention</td>
<td>• Anthropomorphism, autonomy, and ability are positively associated with perceived usefulness.</td>
</tr>
<tr>
<td>Li et al. (2021)</td>
<td>UVT, AT</td>
<td>Human-likeness</td>
<td>Restaurant service</td>
<td>Service encounter evaluation; Revisit intention; Positive word of mouth intention</td>
<td>• Humanlike voice dominantly affects service encounter evaluation, revisit intentions, and word-of-mouth (WOM) intentions.</td>
</tr>
<tr>
<td>Lv et al. (2021)</td>
<td>CAT</td>
<td>Cuteness of AI assistant High vs. Low</td>
<td>Tourism, hospitality</td>
<td>Tolerance of service failure</td>
<td>• Cuteness design of AI assistant affects tolerance of service failure, which is mediated by tenderness and performance expectancy.</td>
</tr>
<tr>
<td>Romero and Lado (2021)</td>
<td>UVT</td>
<td>Anthropomorphism; Social presence</td>
<td>Hospitality</td>
<td>Booking intentions</td>
<td>• Robots reduce contagion risk in hospitality.</td>
</tr>
<tr>
<td>Yoganathan et al. (2021)</td>
<td>SPT, SCT</td>
<td>Humanoid robot vs. self-service machine</td>
<td>Hospitality</td>
<td>Visit intention; Willingness to pay</td>
<td>• Anthropomorphism positively affects expected service quality, first-visit intention, willingness to pay, and increasing warmth/competence inferences, which is moderated by the absence of human staff.</td>
</tr>
<tr>
<td>Zhang, Meng, et al. (2021)</td>
<td>SPT, SoRT, CDVT</td>
<td>Humanity; Social interactivity; Social presence</td>
<td>Public service</td>
<td>Acceptance of AI virtual assistant</td>
<td>• Functionality and social emotions significantly affect trust.</td>
</tr>
<tr>
<td>Fan et al. (2020)</td>
<td>CPT, SReT</td>
<td>Technology anthropomorphism</td>
<td>Check-in service</td>
<td>Consumer dissatisfaction</td>
<td>• There is a inverted-U relationship between perceived humanity and trust; trust mediated the effects of functionality/social emotions on acceptance.</td>
</tr>
<tr>
<td>Lehmann et al. (2020)</td>
<td>UTAUT</td>
<td>Robot appearance</td>
<td>General service</td>
<td>Intention to use</td>
<td>• Older adults have more negative emotions and a more negative attitude in a care situation. Less uncanniness and higher usage intention show for the human-like and android robot.</td>
</tr>
<tr>
<td>Study</td>
<td>Theoretical basis</td>
<td>Robot characteristic orientated factors</td>
<td>Service context</td>
<td>Resultant</td>
<td>Main findings</td>
</tr>
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</tbody>
</table>
| Lin et al. (2020)      | UVT, AIDUATF      | Anthropomorphism; Hedonic motivation; Perceived social influence | Hospitality    | Willingness to the use of AI devices; Objection to the use of AI devices | • Usage intention of AI devices is affected by social influence, hedonic motivation, anthropomorphism, performance/effort expectancy, and emotions.  
• Full-service hotel customers rely less on their social groups than limited service hotel customers when evaluating AI robotic devices.  
• Emotions toward the use of AI device usage are less likely to be influenced by effort expectancy.  
• Emotions cause less impact on objection to AI device use. |
| Roy et al. (2021)      | CAT               | Anthropomorphism; Hedonic motivation; Social influence | Hotel          | Willingness to use AI; Objection to use AI                              | • Three stages of decision-making process exist before customers demonstrate their proclivity to use AI devices/objection to use AI devices.  
• Performance/effort expectancy affect customer emotion, which in turn influence willingness to use AI devices and objection to use AI devices. |
| Gursoy et al. (2019)   | CAT, CDT          | Anthropomorphism; Hedonic motivation; Social influence | General service | Willingness to accept the use of AI devices; Objection to the use of AI devices | • Three-step acceptance generation process is went through in determining the use of AI devices during service interactions.  
• Social influence and hedonic motivation are positively related to performance expectancy; anthropomorphism is positively related to effort expectancy.  
• Performance/effort expectancy significantly affect customer emotions, thereby determining acceptance of AI devices. |
| Lu et al. (2019)       | UTAUT             | Anthropomorphism                          | Hotels, restaurants, airlines, and retail stores | Willingness to use service robots                                       | • Anthropomorphism prominently determines acceptance of service robots.  
• Anthropomorphism thwarts willingness to integrate service robots. |
| Moussawi & Koufaris (2019) | UMITC             | Anthropomorphism; Perceived intelligence | General service | Continuance of use intention                                             | • Two new measures with satisfactory psychometric properties have been developed to assess the user perceptions of PIAs’ intelligence and anthropomorphism. |
| Tussyadiaha & Parkb (2018) | —                 | Anthropomorphism; Animacy; Likeability; Perceived intelligence; Perceived security | Hotel service   | Adoption intention                                                       | • Anthropomorphism, perceived intelligence/security influence robot adoption intention in hotel.  
• NAO’s adoption depends on anthropomorphism & perceived security; Relay’s on perceived intelligence & importance of service operation.  
• The importance of anthropomorphism and perceived security in NAO; perceived intelligence in Relay was found. |

*Note: UTAUT = unified theory of acceptance and use of technology; SPT = Social presence theory; TTF = Task-technology fit theory; UVT = Uncanny valley theory; SET = Social exchange theory; MCT = Mental accounting theory; CT = Complexity theory; RT = Role theory; TAM = Technology acceptance model; AT = Appraisal theory; MET = Media equation theory; SCT = Social cognitive theory; SoRT = Social reaction theory; CDVT = Customer delivered value theory; CPT = Customer participation theory; SReT = Social response theory; AIDUATF = AI devices use acceptance theoretical framework; CAT = Cognitive appraisal theory; CDT = Cognitive dissonance theory; UMITC = Unified model of IT continuance; SRT = Social Relationship Theory*
### Appendix B. Critical Literature Regarding Response to Service Robots

<table>
<thead>
<tr>
<th>Source</th>
<th>Theoretical basis</th>
<th>Antecedents</th>
<th>Mediators</th>
<th>Dependent variables</th>
<th>Moderators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amelia et al. (2022)</td>
<td>UTAUT</td>
<td>Utilitarian aspects (performance expectancy, effort expectancy, facilitating conditions, social influence); Social interaction (animacy/humanness, social intelligence, social presence)</td>
<td>Likeability; Enjoyment of the interaction; Psychological comfort</td>
<td>Customer acceptance of robots; Customer perspective of the company brand</td>
<td>Individual difference (privacy risk, prior experience, technology anxiety, need for human interaction); Task complexity</td>
</tr>
<tr>
<td>Chi et al. (2022)</td>
<td>—</td>
<td>Perceived service influence; Hedonic motivation; Anthropomorphism</td>
<td>Perceived performance expectancy; Perceived effort expectancy; Emotion</td>
<td>Willingness to the use of AI devices; Objection to the use of AI devices</td>
<td>—</td>
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<tr>
<td>Fuentes-Montes et al. (2022)</td>
<td>UTAUT</td>
<td>Museum visitor experience; Empathy; Personal engagement</td>
<td>—</td>
<td>Acceptance of social robots</td>
<td>Age</td>
</tr>
<tr>
<td>Jain et al. (2022)</td>
<td>UGT, ST, PT</td>
<td>Utility features; Hedonic features; Social presence; Perceived privacy risk</td>
<td>Overall perceived value</td>
<td>Voice assistant continued usage intention</td>
<td>Gender; brand credibility (low vs. high)</td>
</tr>
<tr>
<td>Li and Wang (2022)</td>
<td>TAM</td>
<td>Robot characteristics (anthropomorphism, autonomy); Customer characteristics (ability, role clarity)</td>
<td>Perceived usefulness; Perceived ease of use; Customer attitude</td>
<td>Behavioral intention</td>
<td>—</td>
</tr>
<tr>
<td>Liu et al. (2022)</td>
<td>TAM</td>
<td>Trust in AI techniques; Independent personality</td>
<td>Perceived usefulness; Perceived ease-of-use; Perceived enjoyment</td>
<td>Continuation intention</td>
<td>—</td>
</tr>
<tr>
<td>Liu et al. (2022)</td>
<td>—</td>
<td>Perception of robot appearance (warm vs. competent)</td>
<td>Trust</td>
<td>Intention to use</td>
<td>Service context (hedonic-dominant vs. utilitarian-dominant)</td>
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<tr>
<td>Lv et al. (2022)</td>
<td>CDT</td>
<td>AI cuteness (high vs. low)</td>
<td>Social distance; Performance expectancy</td>
<td>Willingness to use</td>
<td>Task type (emotional vs. knowledge-based)</td>
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<tr>
<td>Lv et al. (2022)</td>
<td>Social response theory</td>
<td>Empathic response (high vs. low)</td>
<td>Psychological distance; Trust</td>
<td>Continuous usage intention</td>
<td>Interaction modality (text-only vs. text and voice)</td>
</tr>
<tr>
<td>Nertinger et al. (2022)</td>
<td>—</td>
<td>Anxiety; Attitude; Facilitating conditions; Perceived adaptability; Perceived enjoyment; Perceived ease of use; Perceived usefulness; Trust; Age; Gender; Form of robot introduction; Profession; Years of pet ownership; Experience with robots</td>
<td>—</td>
<td>Acceptance of remote assistive robots</td>
<td>—</td>
</tr>
<tr>
<td>Odekerken-Schröder et al. (2022)</td>
<td>UVT, MET</td>
<td>Anthropomorphism; Social presence</td>
<td>Utilitarian value; Hedonic value</td>
<td>Customer repatronage</td>
<td>FLE interaction quality</td>
</tr>
<tr>
<td>Sonmez (2022)</td>
<td>Construal level theory</td>
<td>Anthropomorphism (high vs. low); Mortality salience (no vs. yes)</td>
<td>—</td>
<td>Trust in autonomous surgical robots;</td>
<td>—</td>
</tr>
<tr>
<td>Source</td>
<td>Theoretical basis</td>
<td>Antecedents</td>
<td>Mediators</td>
<td>Dependent variables</td>
<td>Moderators</td>
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<tr>
<td>Song and Kim (2022)</td>
<td>CASA</td>
<td>Usefulness; social capability; appearance</td>
<td>Attitudes toward HRI; Anticipated service quality</td>
<td>Willingness to undergo autonomous robotic surgery</td>
<td>Anxiety toward robots</td>
</tr>
<tr>
<td>Abou-Shouk et al. (2021)</td>
<td>MM, TPB, TDI, SCT, TAM</td>
<td>Interest in using robots in tourism; General attitude toward technology; Appropriateness of robots to tourism jobs; Perceived enjoyment of using robots; Category of technology adopter</td>
<td>Perceived usefulness of using robots; Perceived easiness of using robots</td>
<td>Retail service robot acceptance</td>
<td></td>
</tr>
<tr>
<td>Blut et al. (2021)</td>
<td>SPT, TTFT, UVT</td>
<td>Consumer traits and predispositions (competence, prior experience, computer anxiety, need for interaction, NARS); Sociodemographics (age, customer gender, education, income); Robot design (physical features (embodiment), nonphysical features (emotion, gaze, gesture, mimicry, voice))</td>
<td>Anthropomorphism; Robot-related mediators (animacy, intelligence, likability, safety, social presence); Functional mediators (case of use, usefulness); Relational mediators (negative affect, positive affect, rapport, satisfaction, trust)</td>
<td>Intention to use</td>
<td>Type of robot: embodiment, robot gender, size, cuteness, design (zoonotic, humanoid); Service context: criticality of service, service type; Method moderators: sampling, stimuli, research design, publication outlet, marketing journal, publication status, country, country innovativeness, year</td>
</tr>
<tr>
<td>Choi et al. (2021)</td>
<td>SET, MCT</td>
<td>Service robot (humanoid vs. non-humanoid); Service failure type; Apology; Explanation</td>
<td>Warmth/competence</td>
<td>Satisfaction; behavioral intention</td>
<td>Human intervention</td>
</tr>
<tr>
<td>Chuah et al. (2021)</td>
<td>CT</td>
<td>Human-likeness (anthropomorphism, perceived intelligence); Technology-likeness (performance expectancy, hedonic motivation, privacy risks); Consumer personalities (extraversion, openness to experience)</td>
<td>—</td>
<td>Behavioral intention to use service robots</td>
<td></td>
</tr>
<tr>
<td>Fernandes and Oliveira (2021)</td>
<td>UVT, UTAUT, RT</td>
<td>Functional elements (perceived ease of use, perceived usefulness, subjective social norms); Social elements (perceived humanness, perceived social interactivity, perceived social presence); Relational elements (trust, rapport)</td>
<td>—</td>
<td>Acceptance of digital voice assistants</td>
<td>Experience pref. human interaction</td>
</tr>
<tr>
<td>Hu (2021)</td>
<td>TPCV, VBDMM</td>
<td>Perceived hedonic value; Perceived utilitarian value</td>
<td>—</td>
<td>Attitude toward using service robots; Future behavioral intention</td>
<td>Previous experience</td>
</tr>
<tr>
<td>Huang et al. (2021)</td>
<td>UVT</td>
<td>Realistic threat; Identity threat</td>
<td>Negative attitude toward the robot</td>
<td>Usage intention</td>
<td>Anthropomorphic appearance of the robot</td>
</tr>
<tr>
<td>Kim et al. (2021)</td>
<td>RCT</td>
<td>Risk of COVID-19 (high vs. low)</td>
<td>Against the robot</td>
<td>Evaluation of/preference for robot-staffed hospital</td>
<td>Subjective perceived threat</td>
</tr>
<tr>
<td>Kwak et al. (2021)</td>
<td>TAM</td>
<td>Hedonically MCI; Functionally MCI; Socially MCI; Cognitive MCI</td>
<td>Perceived value; Attitude</td>
<td>Intention to use</td>
<td>Income level group</td>
</tr>
<tr>
<td>Source</td>
<td>Theoretical basis</td>
<td>Antecedents</td>
<td>Mediators</td>
<td>Dependent variables</td>
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<tr>
<td>Lee et al. (2021)</td>
<td>UTAUT</td>
<td>Functional aspect (performance expectancy, effort expectancy, perceived importance); Emotional aspect (innovativeness, social presence, hedonic motivation)</td>
<td>—</td>
<td>Intention to use robot assistant hotel</td>
<td>—</td>
</tr>
<tr>
<td>Lee, Shechan, et al. (2021)</td>
<td>ECT, CVT, UTAUT, CDT</td>
<td>Technology related personal tendency (personal innovativeness, technology anxiety)</td>
<td>Confirmation, ex-post instrumentality (price value, hedonic motivation, compatibility, perceived security); Satisfaction</td>
<td>Continuance intention; Intention to recommend to others</td>
<td>—</td>
</tr>
<tr>
<td>Lin and Mattila (2021)</td>
<td>GT, CVT, VABT, SRAM</td>
<td>Perceived privacy; Functional benefits; Novelty; Appearance of service robots</td>
<td>Attitude toward service robots; Anticipated overall hotel experience</td>
<td>Acceptance of service robots</td>
<td>—</td>
</tr>
<tr>
<td>Lu et al. (2021)</td>
<td>AT, UVT</td>
<td>Physical appearance (human-likeness); Voice; Language</td>
<td>Perceived credibility; Emotion</td>
<td>Service encounter evaluation; revisit intention; WOM intentions</td>
<td>—</td>
</tr>
<tr>
<td>Meidute-Kavaliauskiene et al. (2021)</td>
<td>TRA</td>
<td>Advantage; Disadvantage; Perceived value</td>
<td>—</td>
<td>Intention to use</td>
<td>—</td>
</tr>
<tr>
<td>Merkle (2021)</td>
<td>CDP, RT, TAM</td>
<td>Ideal service by social robot; Self-service technology; Frontline service employee</td>
<td>—</td>
<td>Functional component (ease of use, usefulness); Informational component (informativeness of interaction); Relational component (benevolence, understanding)</td>
<td>Robot anxiety</td>
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<tr>
<td>Mozafari et al. (2021)</td>
<td>ATT</td>
<td>Service outcome (success vs. failure, failure with recovery)</td>
<td>Responsibility attribution</td>
<td>Usage intention</td>
<td>Service robot design (warm vs. competent)</td>
</tr>
<tr>
<td>Park et al. (2021)</td>
<td>—</td>
<td>Privacy concerns; Trust</td>
<td>Perceived usefulness; Perceived ease of use; Attitude</td>
<td>Behavior intention</td>
<td>—</td>
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<tr>
<td>Pitardi and Marriott (2021)</td>
<td>HCIT, SRT</td>
<td>Perceived usefulness; Perceived ease of use; Enjoyment; Social presence; Social cognition; Privacy</td>
<td>Attitude; Trust</td>
<td>Intention to use</td>
<td>—</td>
</tr>
<tr>
<td>Romero and Lado (2021)</td>
<td>UVT</td>
<td>Anthropomorphism; Social presence; Health history</td>
<td>Health importance; Perceived susceptibility; Prevention efficacy; Attitude</td>
<td>Booking intentions</td>
<td>—</td>
</tr>
<tr>
<td>Roy et al. (2021)</td>
<td>CAT</td>
<td>Social influence; hedonic motivation; Anthropomorphism</td>
<td>Performance expectancy; Effort expectancy; Emotion</td>
<td>Willingness to use AI; Objection to use AI</td>
<td>—</td>
</tr>
<tr>
<td>Seo and Lee (2021)</td>
<td>TAM</td>
<td>Trust</td>
<td>Perceived risk; Customer satisfaction; Perceived usefulness; Perceived ease of use</td>
<td>Behavioral intention</td>
<td>—</td>
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<tr>
<td>Seymour et al. (2021)</td>
<td>UVT</td>
<td>Anthropomorphism</td>
<td>—</td>
<td>Affinity</td>
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</tr>
<tr>
<td>Source</td>
<td>Theoretical basis</td>
<td>Antecedents</td>
<td>Mediators</td>
<td>Dependent variables</td>
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<tr>
<td>Tuomi et al. (2021)</td>
<td>MDJDT, UVT</td>
<td>Extrinsic driver (technological progress, convenience, novelty); Intrinsic driver (more fulfilling jobs, more efficient processes, greater degree of control); Contextual layer; social layer; Interaction layer (tone of voice, gestures, mobility, responsiveness, intent recognition); Psychological layer (social presence, social judgement, peer recognition)</td>
<td>—</td>
<td>Trustworthiness; Preference</td>
<td>—</td>
</tr>
<tr>
<td>Yoganathan et al. (2021)</td>
<td>SPT, SCT</td>
<td>Automated social presence (high vs. low)</td>
<td>Social-cognitive evaluation (perceived warmth, perceived competence, psychological risk, performance ambiguity); Expected service quality</td>
<td>Williness to pay; Visit intention</td>
<td>Human social presence (human staff present vs. human staff absent); Consumer need for interaction with human staff; Consumer technology readiness</td>
</tr>
<tr>
<td>Zhang, Gursoy, et al. (2021)</td>
<td>CAT, AIDUATF</td>
<td>Physical appearance (humanlike, mascot-like, and machine-like)</td>
<td>Performance expectancy; Effort expectancy; Positive emotions;</td>
<td>Willingness to accept the use of service robots</td>
<td>Sense of humor</td>
</tr>
<tr>
<td>Zhang, Meng, et al. (2021)</td>
<td>SPT, SoRT, CDVT</td>
<td>Functionality (perceived usefulness, perceived ease of use); Social emotion (perceived humanity, perceived social interactivity, perceived social presence)</td>
<td>Trust</td>
<td>Acceptance of AI virtual assistant</td>
<td>—</td>
</tr>
<tr>
<td>Danekwerts et al. (2020)</td>
<td>SReT</td>
<td>Perceived personalization; Perceived social presence</td>
<td>Trust (competence, benevolence, integrity); Perceived usefulness; Perceived enjoyment</td>
<td>Usage intention; Service loyalty intention</td>
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</tr>
<tr>
<td>de Kervenoael et al. (2020)</td>
<td>SERVQUAL</td>
<td>Perceived usefulness; Perceived ease of use; Service assurance; Personal engagement; Tangibles; Empathy; Information sharing</td>
<td>Perceived value</td>
<td>Intention to use social robots</td>
<td>—</td>
</tr>
<tr>
<td>Fuentes-Monkeda et al. (2020)</td>
<td>—</td>
<td>Functional, social-emotional, and relational dimensions</td>
<td>—</td>
<td>Service robot acceptance</td>
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<tr>
<td>Fan et al. (2020)</td>
<td>CPT, SReT</td>
<td>Technology anthropomorphism</td>
<td>Blame attribution</td>
<td>Consumer satisfaction</td>
<td>Technology self-efficacy; Interdependent self-construal</td>
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<tr>
<td>Ghazali et al. (2020)</td>
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<td>Liking; Beliefs; Reactance; Attitude; Compliance</td>
<td>Usage intention</td>
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<tr>
<td>Iykov et al. (2020)</td>
<td>—</td>
<td>Expected business outcome; Experience; Service assurance;</td>
<td>—</td>
<td>Willingness to implement service robots</td>
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<tr>
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<tr>
<td>Lee et al. (2020)</td>
<td>TiG, TAM</td>
<td>Perceived ease of use; Perceived usefulness; Subjective norms; Perceived anxiety; Perceived likability</td>
<td></td>
<td>Order adults’ intention to use soft service robot</td>
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<tr>
<td>Lin et al. (2020)</td>
<td>AIDUATF, UVT</td>
<td>Social influence; Anthropomorphism; Hedonic motivation</td>
<td>Performance expectancy; Effort expectancy; Positive emotion</td>
<td>Willingness to the use of AI devices; Objection to the use of AI devices</td>
<td></td>
</tr>
<tr>
<td>Meyer-Waarden et al. (2020)</td>
<td>SERVQUAL, TAM</td>
<td>Tangibles; Competence; Reliability; Responsiveness; Empathy; Credibility</td>
<td>Perceived usefulness; Perceived ease of use; Rust</td>
<td>Intention to reuse</td>
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</tr>
<tr>
<td>Morita et al. (2020)</td>
<td>SERVQUAL</td>
<td>Assurance; Responsiveness; Entertainment factor</td>
<td>Customer satisfaction</td>
<td>Intention to revisit the robot café; Intention to recommend the robot café to others</td>
<td></td>
</tr>
<tr>
<td>Tussyadiah et al. (2020)</td>
<td></td>
<td>Faith in technology; Trusting stance; Negative attitude; Robot form</td>
<td>Trusting beliefs (functionality, helpfulness, reliability)</td>
<td>Trusting intention</td>
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<tr>
<td>Zhong, Zhang, et al. (2020)</td>
<td>TPB, TAM, PVABAM</td>
<td>Usefulness; Ease of use; Sentimental value; Self-efficacy</td>
<td>Attitude; Value; Perceived behavioral control</td>
<td>Behavioral intention</td>
<td>Education; Gender; Experience of hotel robot use; Other robot services</td>
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<tr>
<td>Bruckes et al. (2019)</td>
<td></td>
<td>Structural assurances; Trust in banks</td>
<td>Perceived risk; Initial trust</td>
<td>Intention to use</td>
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<tr>
<td>Gursoy et al. (2019)</td>
<td>CAT, CDT</td>
<td>Social influence; Hedonic motivation; Anthropomorphism;</td>
<td>Performance expectancy; Effort expectancy; Emotion</td>
<td>Willingness to accept the use of AI devices; Objection to the use of AI devices</td>
<td></td>
</tr>
<tr>
<td>Lee et al. (2018)</td>
<td>TAM, PBT, STTMT</td>
<td>Trust; Interactivity; Output quality</td>
<td>Perceived usefulness; Perceived ease of use; Attitude</td>
<td>Acceptance</td>
<td></td>
</tr>
<tr>
<td>Lu et al. (2019)</td>
<td>UTAUT</td>
<td>Performance efficacy; Intrinsic motivation; Anthropomorphism; Facilitating conditions; Emotions</td>
<td></td>
<td>Willingness to use service robots</td>
<td></td>
</tr>
<tr>
<td>Moussawi &amp; Koufaris (2019)</td>
<td>UMITC</td>
<td>Perceived intelligence; Perceived anthropomorphism; Subjective norms</td>
<td>Disconfirmation of expectations; Perceived usefulness; Satisfaction with use</td>
<td>Continuance of use intention</td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>Theoretical basis</td>
<td>Antecedents</td>
<td>Mediators</td>
<td>Dependent variables</td>
<td>Moderators</td>
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<tr>
<td>Tussyadiah &amp; Parkh (2018)</td>
<td>—</td>
<td>Anthropomorphism; Animacy; Likeability; Perceived intelligence; Perceived security</td>
<td>—</td>
<td>Adoption intention</td>
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<tr>
<td>Stock and Merkle (2017)</td>
<td>RT; TAM</td>
<td>Ideal service by social robot; Self-service technology; Frontline service employee</td>
<td>—</td>
<td>Functional component (eas of use, usefulness); Informational component (informativeness of interaction); Relational component (benevolence, user satisfaction, understanding)</td>
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<tr>
<td>Park and Kwon (2016)</td>
<td>TAM</td>
<td>Perceived enjoyment; Service quality</td>
<td>Perceived usefulness; Perceived ease of use; Attitude</td>
<td>Intention to use</td>
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<tr>
<td>Kim and Lee (2014)</td>
<td>TAM, SERVQUAL</td>
<td>Tangible quality; Motion quality; System quality</td>
<td>Perceived usefulness; User intention</td>
<td>Intention to use</td>
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<tr>
<td>Qiu and Benbasat (2009)</td>
<td>SRT</td>
<td>Humanoid embodiment (avatar vs. none); Output modality (human voice vs. TTS vs. text)</td>
<td>Social presence; Trusting beliefs; Perceived usefulness; Perceived enjoyment</td>
<td>Usage intention</td>
<td>Humanoid embodiment (avatar vs. none)</td>
</tr>
</tbody>
</table>

Notes: MCI = motivated consumer innovativeness; UGT = Uses and Gratification theory; ST = Signaling theory; PT = Prospect theory; CASA = Computers-Are-Social-Actor Theory; CDT = Cognitive dissonance theory; MM = Motivation model; TPB = Theory of planned behavior; TDI = Theory of diffusion of innovation; SCT = Social cognitive theory; TAM = Technology acceptance model; UVT = Uncanny valley theory; UTAUT = unified theory of acceptance and use of technology; SPT = Social presence theory; TTFT = Task-technology fit theory; SET = Social exchange theory; CTA = Complexity theory; RT = Role theory; PCD = Perception of consumption Values; VBDMM = Value-based decision-making model; RCT = Rational choice theory; ECT = Expectation-disconfirmation theory; CDP = Confirmation-disconfirmation paradigm; CVT = Consumption value theory; GT = Grounded theory; VABT = Value-attitude-behavior theory; SRAM = Service robot acceptance model; AT = Appraisal theory; CAT = Cognitive appraisal theory; TRA = Theory of Reasoned Action; ATT = Attribution theory; MET = Media equation theory; HCT = Human-Computer Interaction Theories; SRT = Social Relationship Theory; MDJDT = McDonaldization Job design theory; AIDUATF = AI devices use acceptance theoretical framework; SoRT = Social reaction theory; CDVT = Customer delivered value theory; SRCF = Social response theory; CPT = Customer participation theory; TG = theory in general; PVABAM = Perceived value-based acceptance model; UMIFC = Unified model of IT continuance; PBT = Project behavior theory; STTMT = Science and technology task matching theory