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WHAT FACILITATES CONSUMERS ACCEPTING SERVICE ROBOTS? A CONCEPTUAL FRAMEWORK

Research Paper

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Abstract

Confronting with an increasing number of robots swarming into service industries to replace human personnel, studies regarding what drives consumers to use service robots leave to be, unfortunately, still fragmented. Motivated by this, based on a content analysis of the existing studies, this paper establishes a conceptual framework to comprehend the current literature for in-depth understanding concerning customer attitude and their intention to use service robots. Drawing upon a triangulation of perspectives on end-user (i.e., technology user, consumer, and network member) in adoption research, this framework adopts technology acceptance theories, service quality, and expectancy-value theory to set up the skeleton. Furthermore, the antecedents impacting customer acceptance of service robots are subdivided into robot-design, consumer-oriented, relational components, as well as exogenous factors. This paper not only elaborates on the present situation of service robot acceptance research but also promotes it by developing a comprehensive framework regarding the effect factors.

Keywords: Service robot acceptance, Service quality, Robot design, Triangulation view.

1 Introduction

Accompanying the advancement of robotics and artificial intelligence (AI) technology, the number of robots implemented in service encounters is snowballing. Customers progressively orchestrate their daily activities under the aegis of technology, with services growingly equipping AI-enabled applications (Fernandes and Oliveira, 2021). Although the development of service robots is still at the embryonic stage, its growth momentum on the global market is highly promising. A report from Mordor Intelligence (2021) illustrates that the worldwide size of the service robot market is forecasted to reach 213 billion USD by 2026 from 24 billion in 2020, with a cagr of 44.9%. Furthermore, with the outbreak of the Covid-19 pandemic, service robots have been of unprecedented relevance to service sectors by virtue of replacing human employees to perform various tasks of contactless service delivery, as shown in the hospitality (Kim *et al.*, 2021; Romero and Lado, 2021) and healthcare sectors (Kaiser *et al.*, 2021; Tavakoli *et al.*, 2020).

With the rapid diffusion of AI-enabled applications, robotics has been affirmed as the next wave in service technology (Choi *et al.*, 2021; Koo *et al.*, 2021). Investigating service robot acceptance — a dominant topic in customer-robot interactions — presents as an essential conduit helping business practitioners to grasp advantages in fierce market competition (Fernandes and Oliveira, 2021; Huang, Chen, *et al.*, 2021). Whereas the global service robot market proliferates and an increasing number of service robots have been deployed to replace human labor, AI robotics can not only cope with pre-programmed simple services, e.g., information guide, but also go beyond rules for more complex service provision, e.g., customized recommendation (Gursoy *et al.*, 2019; Lv, Luo, *et al.*, 2022). Along with the prospect of robotics being predicted to make a profound revolution in service industries, knowledge remains vague on what drives user adoption of service robots and whether this trend could even keep stubbornly up if increasing robots were deployed (Tussyadiah, 2020). This raises the issue of investigating what fosters customers to accept service robots, which has been a popular area of

investigation that attracts interest from both researchers and practitioners (Belanche et al., 2020; Lu et al., 2020; Wirtz et al., 2018). However, it is still vague regarding facilitators and barriers of accepting robotic service (*r*-service) and whether consumers' satisfaction could be fulfilled if more service robots were adopted in daily service operations. This gives rise to the significance of systematically comprehending what factors determine consumers to use service robots. Accordingly, a comprehensive framework is required to structure the complicated system to integrate the fragmented knowledge concerning the impacts of various factors and gain a complete understanding of consumer attitudes toward and intention to use service robots.

By analyzing 60 empirical studies regarding consumer attitude toward service robots and intention to use service robots/ *r*-services, this research aims to establish a conceptual framework for service robot acceptance. Drawing upon the view of triangulation in technology adoption research, prescribed by Pedersen *et al.* (2002), this work suggests that: i) as a technology user, users' acceptance of service robots depends on the direct influences of human-robot interaction features, which can be either utilitarian aspects of usefulness and ease of use or hedonic aspects, e.g., perceived enjoyment. ii) As a service consumer, service quality delivered by service robots plays a vital part in service commerce, including consumer attitude toward service robots and intention to (re)use/recommend. This directly accounts for the importance of the renowned SERVQUAL dimensions: tangibility, responsiveness, reliability, empathy, and assurance in customer acceptance of service robots. iii) As an interactor, both values of expectancy for success and the subjective task have been considered in the framework based on expectancy-value theory. Apart from the factors standing on the three roles, more antecedents affecting service robot acceptance have been discussed as subgroups: robot-design, customer-orientated, and relational components, as well as several exogenous factors. As an essential note throughout the entire paper, this conceptual framework is applicable in the service robot context by integrating the antecedents next to the fundamental determinants of service robot acceptance.

The remainder of this paper unfolds as follows. The following section delineates a conceptual framework covering fundamental determinants pertaining to the aforementioned three roles that affect consumers' attitudes and intentions to use service robots. Next, we elaborate on the antecedents of service robot acceptance from different perspectives in Section 3. Finally, we conclude this work by discussing the theoretical and practical implications, as well as avenues for future research in Section 4.

2 Framework for consumers' intention to use service robots

Researchers have made great efforts to understand customer adoption and response to robotics in recent years. For instance, Wirtz *et al.* (2018) propose a conceptual adoption model based on user perceptions of using service robots, which subscribes to three-dimension (i.e., functional, social-emotional, and relational) elements affecting customer acceptance, thereby actual use of service robots. Fuentes-Moraleda *et al.* (2020) specify the three dimensions in hotel-specific service robot acceptance. Standing on robot characteristics, Blut *et al.* (2021) put forward a conceptual model for robot adoption based on robot anthropomorphism in service provision. The majority of the current literature concentrates on one or more aspects of service robots, e.g., robot-design characteristics and *r*-service-delivery quality. Despite these efforts, it is notable that the current knowledge on effect factors of robot adoption is still fragmented; more research is called to address the acceptance of robotics in service settings. The insufficiency in research of service robot acceptance further causes a lack of a comprehensive picture of it. Thus, a content analysis regarding related studies is conducive to integrating and extending the current literature on service robot adoption by identifying possible antecedents and theoretical foundations. Accordingly, an extensive literature review is conducted from novel technology-mediated usage, *r*-service, and consumer views. The literature retrieval was performed in Web of Science, Scopus, and AIS Library. Google Scholar was also involved as a supplementary source. After dropping duplicates and unqualified articles, a content analysis was conducted on the remaining 60 studies (Table 1). To gain a comprehensive and in-depth understanding of service robot acceptance among customers, this paper establishes a conceptual framework (Figure 1) based upon previous empirical studies on consumer adoption of either novel technology or service.

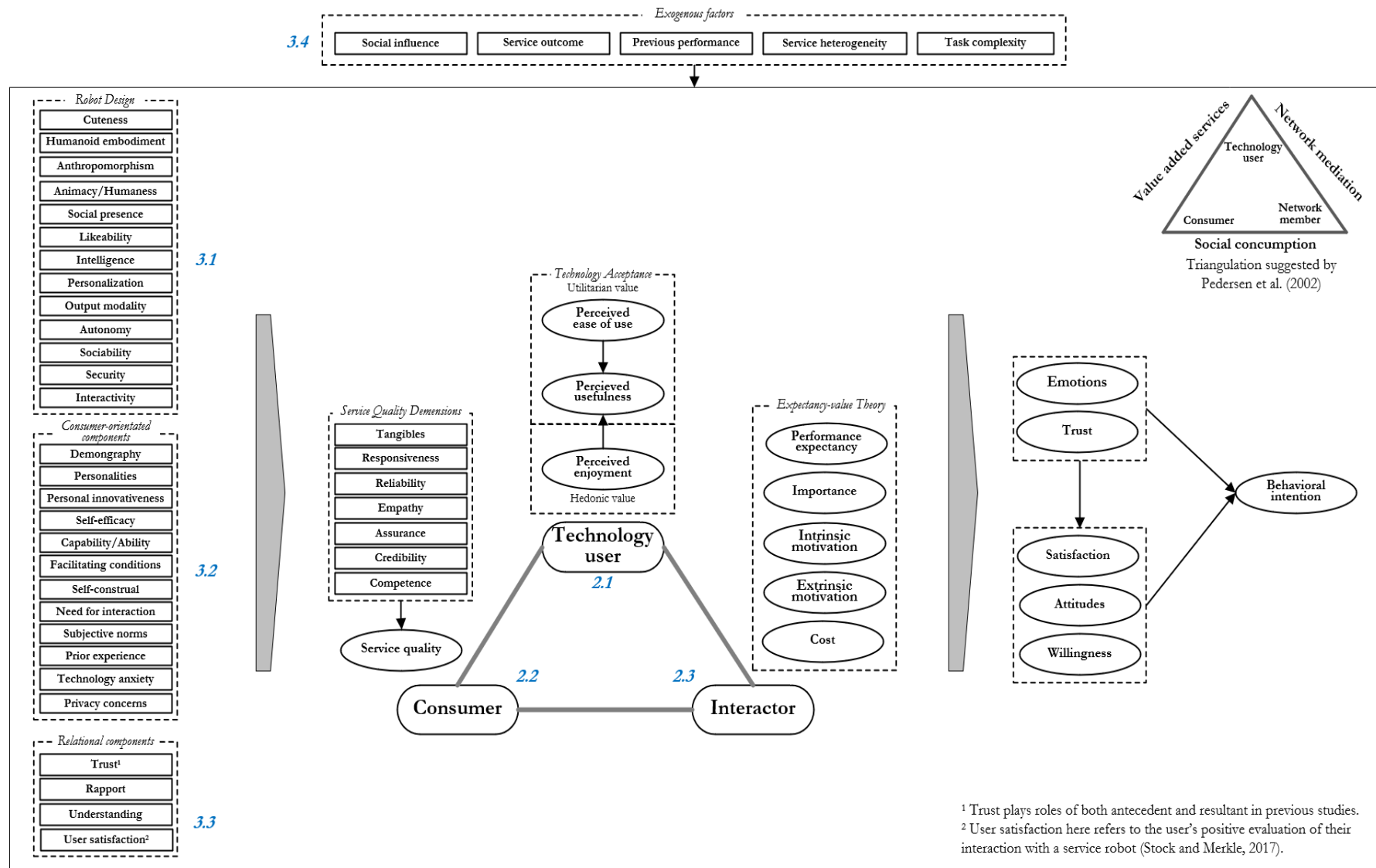


Figure 1. Conceptual framework.

According to Pedersen *et al.* (2002), researchers are required to consider a triangulation of perspectives on end-users in adoption research, i.e., technology user, consumer, and network member. In light of the threefold roles that an individual plays in adoption research, the view of triangulation has been extensively applied in various research fields such as mobile learning (Liu *et al.*, 2010) and mobile commerce (Pedersen *et al.*, 2002). It is also recommended to consider and consolidate theories regarding different roles a user plays (AlHinai *et al.*, 2007). Since the service robot is essentially a kind of novel technology equipped with AI, it is conceivable that a customer of *r*-service is indeed a user of robotic technology. On the other side, as an individual to who a robot deliver service, s/he is naturally a consumer of the *r*-service. In customer-robot interaction, it is worth mentioning that service robots are deployed as regular service providers to replace human personnel in service operations. Unlike traditional technologies like scanners, service robots have several novel capabilities, e.g., adapting external environments and mimicking human cognitive abilities to launch more humanlike interactions (Schuetz and Venkatesh, 2020), which allows them to respond to service requirements by recursively reacting to interactions. In this vein, a customer who is delivered services by a robot also acts as an interactor of bilateral interactions with the robot. A conceptual framework is structured based on the three roles: *technology user*, *consumer*, and *interactor*. This part also specifies the fundamental theories and determinants concerning service robot acceptance.

2.1 Role 1: technology user

The adoption of innovations has set off an intensifying discussion among academics and practitioners from various fields in the recent decades, among which the technology acceptance model (TAM) and its extended theories have been widely accepted. The applicability of TAM has been contended by a substantial body of research, which proves to be valid to predict the acceptance of different information technology innovations and services, e.g., e-service (Ladhari, 2010), mobile learning (Liu *et al.*, 2010), online shopping (Perea *et al.*, 2004), and NetBank (Lee, 2009). The original version of TAM (Davis, 1989) is set up from utilitarian/functional value. It endorses that the two specific constructs, i.e., perceived usefulness and ease of use, are the fundamental determinants for user acceptance that directly affect personal attitudes towards information technology, further impacting behavioral intention, thereby actual behavior to use the technology. Concretely, perceived usefulness is conceptualized as “*the degree to which a person believes that using a particular system would enhance his or her job performance*” (Davis, 1989, p. 320); ease of use refers to “*the degree to which a person believes that using a particular system would be free of effort*” (Davis, 1989, p. 320).

In addition to the two initially identified core factors, more recent technology acceptance models also consider the hedonic value. Perceived enjoyment is included as a significant construct, referring to “*the extent to which the activity of using the technology [emphasis added] is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated*” (Davis *et al.*, 1992, p. 1113). Thereby, the TAM paradigm covers both values of utilitarianism and hedonism. The three constructs dominate personal attitude toward using innovations, which has been debated has a strong, direct, and positive impact on behavioral intentions, and thus actual usage behavior of innovations (Bobbitt and Dabholkar, 2001; Davis, 1993; Monsuéré *et al.*, 2004).

Given that robots are essentially an AI-driven technological innovation, technology acceptance models are widely utilized to investigate factors that affect the adoption of service robots or *r*-services (Kim *et al.*, 2021; Tussyadiah, 2020). TAM provides a firm theoretical grounding for understanding consumer intention to use service robots in different service scenarios (Lin and Mattila, 2021). As proof, TAM (Davis, 1989), along with self-service technology theory (SST) (Meuter *et al.*, 2005), underlie the theoretical foundation for many studies to contrive complex conceptual models, e.g., the service robot acceptance model (sRAM) (Wirtz *et al.*, 2018), the hotel-specific sRAM (Fuentes-Moraleda *et al.*, 2020), and the AI device use acceptance model (AIDUA) (Gursoy *et al.*, 2019). Nevertheless, the practicability of TAM is unfortunately still limited by its parsimoniousness. As a result, numerous researchers typically take other factors, in particular as antecedents, into account to improve the explanatory power of research models by integrating theories of relevance, for example, theory of planned behavior (Zhong *et al.*, 2020), theory of diffusion of innovation (Abou-Shouk *et al.*, 2021),

role theory (Stock and Merkle, 2017), confirmation-disconfirmation theory (Merkle, 2021), social cognitive theory (Abou-Shouk *et al.*, 2021), uncanny valley theory (UVT) (Lin *et al.*, 2020), consumption value theory (Lee *et al.*, 2021), SERVQUAL paradigm (Meyer-Waarden *et al.*, 2020). With this in mind, it can be concluded that TAM can be utilized as a critical branch to build the conceptual framework in the present work.

2.2 Role 2: consumer

Despite several usage scenarios for service robots nowadays, robot use for commercial value accounts for the main proportion, especially in the hospitality and restaurant industries (e.g., Ivkov *et al.*, 2020; Odekerken-Schröder *et al.*, 2021; Tuomi, Tussyadiah and Stienmetz, 2021). As mentioned, service robots are deployed to assist or replace human employees to deliver services for customers. With this regard, service robot users act as consumers having purchased the *r*-service, for who the perceived service quality plays the core role in service experience, affecting their satisfaction with the service and behavioral intention to (re)visit the service (Moussawi and Koufaris, 2019; Park and Kwon, 2016). Service quality here can be simplified as the overall evaluation of service performance (Santos, 2003), similar to the conceptualization from Zeithaml *et al.* (1985) that the quality is judged in light of excellence and superiority.

Within the adoption of service robots, a research stream of the reviewed studies suggests delivered *r*-service quality impacts customers' perception of overall quality, thus influencing their intention to accept (e.g., Park and Kwon, 2016; Yoganathan *et al.*, 2021). Specifically, several researchers borrow well-known theories from traditional human-delivered services for the delivered quality, which are headed by SERVQUAL consisting of tangibility, responsiveness, reliability, empathy, and assurance (Parasuraman *et al.*, 1988). Morita *et al.* (2020) extend SERVQUAL by integrating entertainment factors and interactivity, and conclude that assurance and responsiveness significantly trigger customer satisfaction, further increasing revisit and recommendation intention. De Kervenoael *et al.* (2020) empirically evidence that empathy (directly), service assurance (indirectly), and tangibles (indirectly) positively influence intention to use social robots through the mediator of perceived value. Kim and Lee (2014) contend that tangible quality, motion quality (responsiveness and assurance), and system quality significantly influence perceived usefulness and user satisfaction, thus contributing to a higher intention to use service robots. Similarly, Meyer-Waarden *et al.* (2020) develop a seven-dimensional service quality by including competence and credibility and verify that tangibles and reliability affect intention to reuse chatbots through perceived usefulness and ease of use, while credibility contributes to trust in the chatbots. Meanwhile, a few studies focus on infrastructure on service robots. Yoganathan *et al.* (2021) manifest that the humanoid level of robots can affect consumers' social cognitive evaluation and expected service quality, thereby impacting willingness to pay and visit intention.

2.3 Role 3: interactor

The process of *r*-service delivery is, in essence, a process of iteratively bilateral interactions between the customer and the robot. A service robot user gains the role of *interactor* that is assigned a "task" to navigate the robot to have it respond to service requirements. As such, customers may exhibit differentiating assessments of the attractiveness of task outcomes. Those valuing the result would be more driven to get the outcome, which is highly likely to make up for low probabilities of success and perceived monetary/nonmonetary costs. Oppositely, although people feel capable of accomplishing a task, they might not participate if they perceive a low task value (Cole *et al.*, 2008). As a long-standing perspective on motivation, the expectancy-value theory asserts that "*individuals' choice, persistence, and performance can be explained by their beliefs about how well they will do on the activity and the extent to which they value the activity*" (Wigfield and Eccles, 2000, p. 68). This theory can be applied as a theoretical lens to structure several of the reviewed studies. Achievement behavior is determined by two core aspects: expectation for success and subjective task value (including four sub-values: incentive and attainment value, intrinsic value, utility value, and cost)(Eccles and Wigfield, 1995).

Study	Research focus	Theoretical foundation	Sampling	Antecedents	Mediators/Moderators	Resultants
Jain <i>et al.</i> (2022)	Continual adoption of voice assistant	Uses and Gratification theory; Signaling theory; Prospect theory	Online survey ($N = 1,820$)	Utility features; Hedonic features; Social presence; Perceived privacy risk	Overall perceived value; Gender; Brand credibility	Continual usage intention
Liu <i>et al.</i> (2022)	Adoption of service robots	—	Experiment ($N1 = 206$; $N2 = 367$)	Perception of robot appearance (warm vs. competent)	Trust; Service context (Hedonic-dominant vs. utilitarian-dominant)	Intention to use
Lv <i>et al.</i> (2022)	The influence of cuteness on AI application acceptance	Cognitive dissonance theory	Experiments ($N1 = 71$; $N2 = 86$; $N3 = 73$; $N4 = 97$; $N5 = 87$; $N6 = 86$; $N7 = 93$; $N8 = 85$)	AI cuteness (high vs. low)	Social distance; Performance expectancy; Task type (emotional vs. knowledge-based)	Willingness to use
Abou-Shouk <i>et al.</i> (2021)	Adoption of service robots	Motivation model; Theory of planned behavior; Theory of diffusion of innovation; Social cognitive theory; TAM	Survey ($N = 570$)	General attitude toward technology; Appropriateness of robots to tourism jobs; Perceived enjoyment of using robots; Category of technology adopter; Interest in using robots in tourism	Perceived usefulness; Perceived easiness	Attitude towards robot's usage
Amelia <i>et al.</i> (2021)	Customer acceptance of frontline service robots	Acceptance of technology	Observations ($N = 26$); Focus groups ($N = 26$); Interviews ($N = 15$)	Utilitarian aspects (social influence, effort expectancy, performance expectancy, facilitating conditions); Social interaction (animacy/humanness, social intelligence, social presence); Individual and task heterogeneity (individual differences, e.g., privacy risk, prior experience with SST, technology anxiety, need for human interaction; task complexity)	Customer responses towards service robots (likeability, enjoyment, psychological comfort)	Customer acceptance
Blut <i>et al.</i> (2021)	Customer response to anthropomorphism in service provision	Social presence theory; Task-technology fit theory; theory of anthropomorphism; UVT	Literature retrieval ($N = 71$)	Anthropomorphism	Animacy; Intelligence; Safety; Likability; Social presence; Ease of use; Usefulness; (Negative or positive) affect; Rapport; Satisfaction; Trust	Intention to use
Choi <i>et al.</i> (2021)	Customer response to service robots	Social exchange theory; Mental accounting theory	Scenario-based experiments ($N1 = 205$; $N2 = 205$; $N3 = 212$)	Service robot (humanoid vs. non-humanoid)	Warmth (competence); Human intervention; Service failure type; Apology; Explanation;	Satisfaction; Behavioral intention
Chuah <i>et al.</i> (2021)	Complexity of consumers' intention to use service robots	Complexity theory	Online survey via social media ($N = 566$)	Anthropomorphism; Perceived intelligence; Performance expectancy; Hedonic motivation; Privacy risks; Extraversion; Openness to experience	—	Behavioral intention
Fernandes and Oliveira (2021)	Consumers' acceptance of digital voice assistants	UVT; Technology acceptance theories; Role theory	Survey ($N = 238$)	Perceived Ease of Use; Perceived Usefulness; Subjective Social Norms; Perceived Humanness; Perceived Social Interactivity; Perceived Social Presence; Rapport; Perceived Trust	—	Customer Acceptance
Fuentes-Moraleda <i>et al.</i> (2021)	Willingness to accept social robots in museum contexts	Technology acceptance models	Survey ($N = 433$)	Perceived utility; Perceived ease of use; Perceived value; Information exchange; Service guarantee; Tangibles; Personal commitment	—	Intention of use
Ge <i>et al.</i> (2021)	Human-robot interaction of financial-advising services	—	Field study ($N = 4,374$)	Previous investment performance; Investors' capability; Usage adjustment	—	Adoption; Investment performance
Hu (2021)	Human-robot service	Theory of perceived consumption	Online surveys ($N1 = 129$;	Perceived hedonic value; Perceived	Previous experience; Industry	Attitude toward using

Study	Research focus	Theoretical foundation	Sampling	Antecedents	Mediators/Moderators	Resultants
	interaction	Values; Value-based decision-making model	N2 = 268)	utilitarian value	context (utilitarian/hedonic)	service robots; Behavioral intention
Huang <i>et al.</i> (2021)	Adoption of hotel service robots	UVT	Experiment (N = 262)	Realistic threat; Identity threat,	Negative attitude; Anthropomorphic appearance	Usage intention
Kim <i>et al.</i> (2021)	Preference for robot service in hospitality	Rational choice theory	Online surveys (N _{sum} = 864)	High (vs. low) risk of Covid-19	Concerns on safety and social distancing; Subjective perceived threat	Evaluation of/ preference for robot-staffed hotel
Kwak <i>et al.</i> (2021)	Acceptance of service robot	TAM	Online survey (N = 243)	Functionally/ Hedonically/ Socially / cognitively motivated consumer innovation	Perceived value; Attitude; Income level	Intention to use
Lee <i>et al.</i> (2021)	Customer perceptions of using hotel assistant robots	—	Survey (N = 494),	Facilitating conditions; Performance; Social presence; expectancy; Innovativeness; Perceived importance; Hedonic motivation	—	Intention to use robot assistant hotel
Lee, Sheehan, <i>et al.</i> (2021)	Post-acceptance of AI-based voice assistant systems	Expectation-confirmation theory; Consumption value theory; Technology acceptance theories; Cognitive dissonance theory	Survey (N = 400)	Personal innovativeness; Technology anxiety	Confirmation; Perceived value; Hedonic motivation; Compatibility; Perceived security; Satisfaction	Intention to recommend; Continuance intention
Li and Wang (2021)	Customer acceptance of service robots	TAM	Online survey (N = 406)	Anthropomorphism; Autonomy; Role clarity; Ability	Perceived usefulness; Perceived ease of use; Customer attitude	Behavioral intention
Lin and Mattila (2021)	The value of service robots from the guest's perspective	Grounded theory; Theory of consumption values; Value-attitude-behavior theory; Service robot acceptance model	Interview (N = 30); Online survey (N = 215)	Perceived privacy; Functional benefits; Novelty value; Appearance of service robots	Attitude toward service robots; Anticipated overall hotel experience	Acceptance of service robots
Lin <i>et al.</i> (2021)	Customer response to service robots	Uncertainty reduction theory	Scenario-based experiment (N = 190)	Personal innovativeness; Service heterogeneity	Perceived risk	Revisit intention
Lu <i>et al.</i> (2021)	the impact of robot human-likeness on customer response	Appraisal theory; UVT	Experiment (N = 587)	Physical appearance; humanlike voice; humanlike language style	—	Service encounter evaluation; Revisit/ WOM intentions
Meidute-Kavaliauskiene <i>et al.</i> (2021)	Customer perception of service robots	Theory of Reasoned Action	Online survey (N = 1,408)	Perceived advantage; Perceived disadvantage; Perceived value	—	Intention to use
Merkle (2021)	Service Robot Acceptance	Confirmation-disconfirmation paradigm; Role theory; TAM	Interview (N = 63); Experiment (N = 90)	Functional component (Ease of use, usefulness); Informational component (informativeness of interaction); Relational component (benevolence, understanding)	Robot anxiety	Robot acceptance
Mozafari <i>et al.</i> (2021)	Customer response to r-service	Attribution theory	Experiment (N = 325)	Service outcome (success vs. failure vs. failure with recovery)	Responsibility attribution; Warm vs. Competent	Usage intention
Odekerken-Schröder <i>et al.</i> (2021)	Customer response	UVT; Media equation theory	Filed study (N = 108); scenario-based experiment (N = 361)	Anthropomorphism; Social presence;	Utilitarian value; Hedonic value; Frontline employees interaction quality	Customer patronage
Park <i>et al.</i> (2021)	Adoption of AI service robots	—	Scenario-based online survey (N = 517)	Privacy concern	Trust; Perceived ease of use; Perceived usefulness; Attitude	Behavior intention
Pitardi and Marriott (2021)	Acceptance of service robots	Human-Computer Interaction Theories; Social Relationship Theory	Online survey (N = 466)	Perceived usefulness; Perceived ease of use; Enjoyment; Social presence; Social cognition; Privacy	Attitude; Trust	Intention to use
Romero and Lado (2021)	Guests' perceptions about robots' COVID-19 prevention efficacy	UVT	Scenario-based experiment (N = 711)	Anthropomorphism; Social presence, Health history	Health importance; Perceived susceptibility; Prevention efficacy; Attitude	Booking intentions
Seo and Lee (2021)	Customer acceptance of service robots	TAM	Scenario-based online survey (N = 338)	Trust; Perceived risk	Perceived usefulness; Perceived ease of use	Customer satisfaction; Behavioral intention

Study	Research focus	Theoretical foundation	Sampling	Antecedents	Mediators/Moderators	Resultants
Tuomi <i>et al.</i> (2021)	Humanoid robot adoption in hospitality service encounters	McDonalldization Job design theory; UVT	Exploratory service experimentation ($N1 = 30$; $N2 = 18$)	Contextual layer (concept and task fit); Social layer (degree of agency, locus of control); Interaction layer (tone of voice, gestures, mobility); Psychological layer (social pressure, social judgment, peer recognition); Extrinsic driver (technological progress, convenience, novelty); Intrinsic driver (more fulfilling jobs, more efficient Percoesses, greater degree of control)	—	Humanoid robot adoption
Yoganathan <i>et al.</i> (2021)	Effects of automated social presence	Social presence theory, Social cognition theory	Scenario-based experiment ($N = 300$)	Humanoid robots (vs. self-service machines)	Expected service quality	Visit intention; Willingness to pay
Zhang, Gursoy, <i>et al.</i> (2021)	Customer acceptance of AI service robots	Cognitive appraisal theory; AI devices use acceptance theoretical framework	Experiment ($N = 251$); Scenario approach ($N = 391$)	Robot appearance (humanlike, mascot-like, machine-like)	Effort expectancy; Emotions; Sense of humor	Willingness to accept
Zhang, Meng, <i>et al.</i> (2021)	Acceptance of AI Virtual Assistants	Social presence theory; Social reaction theory; Customer delivered value theory	Survey ($N = 240$)	Perceived usefulness, Perceived ease of use, Perceived humanity; Perceived social interactivity, Perceived social presence	Trust	Acceptance
Chi <i>et al.</i> (2022)	AI Device Acceptance Works	—	online survey ($N = 423$)	Social Influence; Hedonic Motivation; Anthropomorphism	Performance Expectancy; Effort Expectancy; Emotion	Willingness to Use; Objection of Use
Danckwerts <i>et al.</i> (2020)	Impacts of recommendation chatbot characteristics	Social response theory	Survey ($N = 177$)	Perceived personalization; Perceived social presence	Trust (integrity, competence, benevolence); Perceived usefulness; Enjoyment	Usage intention, Service loyalty intention
de Kervenoael <i>et al.</i> (2020)	Human-robot interaction in hospitality services	SERVQUAL	Semi-structure interview ($N = 5$); Survey ($N = 443$)	Empathy; Information Sharing; Perceived Usefulness; Perceived Ease of Use; Service Assurance; Personal Engagement; Tangibles	Perceived Value; Age; Education; Gender	Intention to use social robot
Fuentes-Moraleda <i>et al.</i> (2020)	Acceptance of hotel service robots	—	Online reviews ($N = 7994$)	Functional dimension; Relational dimension, Social-emotional dimension	—	Customer acceptance of service robots
Fan <i>et al.</i> (2020)	Customer response to service robots	customer participation theory; social response theory	Online survey ($N = 261$)	Technology anthropomorphism	Blame attribution; Technology self-efficacy; Interdependent self-construal	Customer dissatisfaction
Ghazali <i>et al.</i> (2020)	Acceptance of persuasive robots	TAM	Experiment ($N = 78$)	Liking; Reactance; Usefulness; Ease; Enjoy	Attitude; Beliefs; Compliance	Intentions
Ivkov <i>et al.</i> (2020)	Attitudes towards Service Robotization	—	online survey ($N = 263$)	Experience, Expected Business Outcome; Service Assurance; Empathy; Reliability; Communication and Interaction; Tangibles; Social Influence; Performance	—	Willingness to implement service robots
Lee <i>et al.</i> (2020)	Adoption of soft service robots in Older adults	theory in general, TAM	Survey ($N = 79$)	Perceived ease of use; Perceived usefulness; Subjective norms; Perceived anxiety; Perceived likability	—	Intention to use soft service robot
Lehmann <i>et al.</i> (2020)	Attitudes of Older Adults Toward Robots	Technology acceptance theories	Vignette methodology and survey ($N = 142$)	Robot appearance; Service situations	—	Emotions & Attitudes toward robots
Lin <i>et al.</i> (2020)	Acceptance of AI robotic device use in hotels	AI Device Use Acceptance theory; UVT	Survey ($N = 605$)	Social Influence; Hedonic Motivation; Anthropomorphism;	Performance Expectancy; Effort expectancy; Emotion	Willingness to use, Objection of Use
Mele <i>et al.</i> (2020)	Acceptance/rejection of service robots	acceptance theory	Interviews ($N = 190$); Surveys ($N = 75$); online reviews ($N = 265$)	Perceived usability; Ease of use; Social norms; Social presence; Humanness; Perceived sociability; Emotions; Trust; robot rapport; Value-in-context	—	Robot acceptance

Study	Research focus	Theoretical foundation	Sampling	Antecedents	Mediators/Moderators	Resultants
Meyer-Waarden <i>et al.</i> (2020)	Customer Acceptance	SERVQUAL; TAM	Online survey (<i>N</i> = 146)	Tangibles; Competence; Reliability; Responsiveness; Empathy; Credibility	Perceived usefulness; Perceived ease of use; Trust	Intention to reuse
Morita <i>et al.</i> (2020)	R-service quality evaluation	SERVQUAL	Survey (<i>N</i> = 95)	Tangibles; Reliability; Assurance; Responsiveness; Empathy; Interactivity; Entertainment factor	Customer satisfaction	Intention to revisit; Intention to recommend;
Roy <i>et al.</i> (2020)	Customer Acceptance of Use of AI devices in Hospitality Services	Cognitive appraisal theory	Survey (<i>N</i> = 210)	Social influence; Hedonic motivation; anthropomorphism	Performance expectancy; Effort expectancy; Emotion	Willingness to Use AI, Objection to use AI
Zhang (2020)	Public perceptions of service robots during Covid-19 pandemic	—	Online reviews (<i>N</i> = 3948)	Health factor; Societal factors	—	Adoption of service robots
Zhong, Zhang, <i>et al.</i> (2020)	Acceptance of service robots in hotel industries	Theory of planned behavior; TAM; Perceived value-based acceptance model.	Survey (<i>N</i> = 217)	Usefulness; Ease of use; Sentimental value; Self-efficacy	Attitude; Perceived value; Perceive behavioral control	Behavioral Intention
Bruckes <i>et al.</i> (2019)	Adoption of Robo-advisors service in banks	—	Survey (<i>N</i> = 246)	Structural assurances; Trust in Banks	Perceived Risk; Initial Trust	Intention to use
Gursoy <i>et al.</i> (2019)	Acceptance of AI device use in service delivery	Cognitive Appraisal Theory; Cognitive Dissonance Theory	Online survey (<i>N</i> = 439)	Social Influence; Hedonic Motivation; Anthropomorphism	Performance Expectancy; Effort expectancy; Positive emotion	Willingness to use; Objection of Using AI Devices
Lu <i>et al.</i> (2019)	Service robot integration willingness scale	Technology acceptance theories	Survey (<i>N</i> = 1,348)	Performance efficacy; Intrinsic motivation; Anthropomorphism; Social influence; Facilitating conditions; Emotions	—	Willingness to use service robots
Merkle (2019)	Customer response to r-service	Attribution theory; Expectation disconfirmation theory	Experiment (<i>N</i> = 120)	Service provider (robots vs. employees); Service situation (appropriate vs. failure)	—	Customer satisfaction
Moussawi & Koufaris (2019)	Scale development and validation for Personal Intelligent Agents	Unified model of IT continuance	Survey (<i>N</i> = 232)	Perceived intelligence; Perceived anthropomorphism; Subjective norms	Perceived usefulness; Satisfaction with use; Disconfirmation of expectation	Continuance of use intention
Lee <i>et al.</i> (2018)	Customer acceptance of restaurant robotics	TAM; Project behavior theory; Science and technology task matching theory	Survey (<i>N</i> = 382)	Trust; Interactivity; Output quality	Perceived usefulness; Attitude; Perceived ease of use	Acceptance
Tussyadiaha & Parkb (2018)	Adoption of hotel service robots	—	Online survey (<i>N</i> = 841); Laboratory experiment (<i>N</i> = 32)	Anthropomorphism; Animacy; Likeability; Perceived intelligence; Perceived security; Importance of operations	—	Adoption intention
Stock and Merkle (2017)	R-service quality	Role theory; TAM	Experiment (<i>N</i> = 82)	Functional (Ease of use, usefulness); Informational (informativeness of interaction); Relational (benevolence, user satisfaction, understanding)	—	Robot acceptance
Park and Kwon (2016)	Adoption of teaching assistant robots	TAM	Survey (<i>N</i> = 609)	Perceived enjoyment; Service quality; Perceived usefulness; Perceived ease of use	Attitudes	Intention to use
Kim and Lee (2014)	Service quality on personal robot service	TAM; SERVQUAL	Survey (<i>N</i> = 490)	Tangible quality (tangibles); Motion quality (responsiveness + assurance); System quality	User satisfaction; perceived usefulness	Intention to use
Qiu and Benbasat (2009)	Acceptance of anthropomorphic product recommendation agents	Social relationship	Laboratory experiment (<i>N</i> = 168)	Humanoid embodiment (avatar vs. none); Output modality (human voice vs. TTS vs. text)	Social presence; Trusting beliefs; Perceived enjoyment; Perceived usefulness	Usage intentions

Table 1. Review on service robot acceptance

In the reviewed literature, the expectation for success has been projected to performance expectancy, which refers to *the extent to which one's belief that adopting a specific technology/service would allow them to successfully achieve the given tasks* (Venkatesh *et al.*, 2003). On the other hand, subjective task value can be unfolded as follows: i) arising from the importance of doing well on the task, attainment value has been identified to contribute to consumer intention to use service robots (Lee, Lee, *et al.*, 2021; Tussyadiah and Parkb, 2018). ii) Intrinsic value cares more about one's internal perceptions of using innovations, defined as *the pleasure received while interacting with a technological device*, which is valid to predict users' technology use in the consumer context (Lu *et al.*, 2019). As Lu *et al.* (2019) noted, consumers classify service robots as more of a hedonic system such that *intrinsic motivation dominates user acceptance at the expense of extrinsic motivation*. The reviewed literature has reported that such constructs as intrinsic motivation (Lu *et al.*, 2019) and hedonic dimensions (e.g., perceived enjoyment, which is overlapped with the hedonic value of TAM) (e.g., Abou-Shouk *et al.*, 2021; Pitardi and Marriott, 2021). iii) Utility value accounts for the extrinsic motivation that affects robot use. Tuomi *et al.* (2021) identified extrinsic drivers (i.e., technological progress, convenience, and novelty) as determinants of humanoid robot adoption in hospitality. iv) Cost interprets cognitive and emotional dimensions that users need to pay for accomplishing the activity. As an example, effort expectancy (e.g., Amelia *et al.*, 2021; Zhang, Gursay, *et al.*, 2021), fear of privacy invasion (e.g., Jain *et al.*, 2022; Park *et al.*, 2021), and perceived threat, including general threat (Kim *et al.*, 2021), as well as realistic threat and identity threat (Huang, Cheng, *et al.*, 2021), have been reported in prior studies.

3 Antecedents of service robot acceptance

By a content analysis of the literature, we can first conclude that a consensus regarding determinants of *r*-service acceptance has not been reached yet. However, several frequently identified determinants in previous studies can be framed from a triangulation of perspectives. Second, numerous antecedents affect customer perceptions of and responses to service robots. According to past studies (Belanche *et al.*, 2020; Romero and Lado, 2021), customer acceptance of robots is primarily studied in the light of robot-, customer-, and service encounter-related factors. Bearing this in mind, we subdivide the antecedents of service robot acceptance into robot-design, consumer-orientated, and relational components. Several exogenous factors have also been considered in the framework as a supplement.

3.1 Robot-design components

Many of the reviewed articles highlight the importance of robot-design factors, from appearance to functionality, in affecting people's acceptance of service robots, from attitudes toward robots to intention to use a robot. Several recent studies emphasize the role of cuteness, from graphics to voice cues, playing in robot-human interactions (Liu *et al.*, 2022; Lv *et al.*, 2021; Lv, Luo, *et al.*, 2022). For instance, Lv *et al.* (2022) verify the effect of AI cuteness on willingness to use via the mediators of social distance and performance expectancy. Cuteness has also proved to increase customer tolerance of service failure (Lv *et al.*, 2021). In addition, the UVT (Mori, 1970) and visual cue theory (Breazeal *et al.*, 2005) have been widely applied to understand the effect of humanlikeness/machinelikeness level in robots on customer intentions to use (Belanche *et al.*, 2020; Lin and Mattila, 2021; Yu, 2020). For example, with experimental evidence, Zhang *et al.* (2021) find that the physical (human-/mascot-/machine-like) appearance of robots significantly impacts consumer willingness to accept the use of service robots through performance expectancy, effort expectancy, and emotions. Lu *et al.* (2021) show that a humanlike appearance triggers higher customer evaluation of service encounters and higher revisit intention to the *r*-service.

The terminology *anthropomorphism* can be one of the most frequently considered constructs in the reviewed literature, known as the extent of robotics having human characteristics concerning either physical appearance or psychological features (Lu *et al.*, 2019). It has been identified as a role of high significance in service robot acceptance and adoption, determining consumer trust (Blut *et al.*, 2021; Meyer-Waarden *et al.*, 2020), satisfaction (Choi *et al.*, 2021; Fan *et al.*, 2020), willingness to use (Gursoy *et al.*, 2019; Lu *et al.*, 2019), attitudes (Romero and Lado, 2021), and behavioral (continuance)

intention to use service robots (Chuah *et al.*, 2021; Moussawi and Koufaris, 2019; Tussyadiaha and Parkb, 2018). Similar constructs, e.g., humanness (Amelia *et al.*, 2021; Fernandes and Oliveira, 2021; Mele *et al.*, 2020), humanoid (Choi *et al.*, 2021; Qiu and Benbasat, 2009), humanlike (Lu *et al.*, 2021), animacy (Amelia *et al.*, 2021), and social presence (Fernandes and Oliveira, 2021; Mele *et al.*, 2020; Romero and Lado, 2021), have also been investigated by previous studies.

A handful of studies focus on the effects of robot-functionality features on service robot acceptance. For example, conceptualized as *the level at robots can learn, reason, and solve problems*, robot intelligence has been identified as a determinant of customer satisfaction (Moussawi and Koufaris, 2019) and intention to (continuance) use a robot (Amelia *et al.*, 2021; Blut *et al.*, 2021; Chuah *et al.*, 2021). As an agent of customization, personalization can be viewed as *the degree to which users perceive that a service robot meets personal requirements*, which plays a central role in user's evaluation and acceptance of robots, including trust, usage intention, and service loyalty intention (Danckwerts *et al.*, 2020). Output modality has also been emphasized in prior studies as a crucial functional factor dominating service robot adoption (Qiu and Benbasat, 2009). Specifically, the humanlike voice and language of service robots determine customer evaluation (Lu *et al.*, 2021) and (re)use intention (Lu *et al.*, 2021; Qiu and Benbasat, 2009). In addition, some other antecedents that affect service robot acceptance have also been explored in the reviewed literature, including autonomy (Li and Wang, 2021), likeability (Tussyadiaha and Parkb, 2018), sociability (Mele *et al.*, 2020), security (Lee, Sheehan, *et al.*, 2021; Tussyadiaha and Parkb, 2018), interactivity (Fernandes and Oliveira, 2021; Morita *et al.*, 2020), etc.

3.2 Consumer-orientated components

As one side of human-robot interaction, customers' personal attributes undoubtedly affect their service robot acceptance, no matter as a technology user, service consumer, or interactor. First, user traits that attract researchers' interest in understanding service robot adoption include demography and personal characteristics. Concretely, such demographics as age and education are asserted to moderate the relationship between personal engagement/tangibles and perceived value, while education and gender moderate the effect of perceived value on the usage intention of social robots (de Kervenoael *et al.*, 2020). Apart from demography, some studies focus on the impact of personalities, e.g., extraversion and openness to experience, on behavioral intention to use service robots (Chuah *et al.*, 2021).

More studies turn to the roles relevant personal characteristics play in service robot adoption. For example, personal innovativeness, as an individual trait reflecting one's willingness to try novel technology (Lin *et al.*, 2021), plays an essential role in determining customer (re)use intention and recommendation intention of service robots (Lee, Sheehan, *et al.*, 2021; Lin *et al.*, 2021). Likewise, self-efficacy, or one's confidence in their capabilities and resources to successfully handle a particular task, influences customer satisfaction (Fan *et al.*, 2020) and intention to use service robots (Zhong *et al.*, 2020). Similar constructs like capability (Li and Wang, 2021) and ability (Ge *et al.*, 2021) have also been investigated in the reviewed studies. Facilitating conditions, conceptualized by the control, resources, and knowledge that encourage one to use a service, foster intention to use robots (Amelia *et al.*, 2021; Lee, Lee, *et al.*, 2021; Lu *et al.*, 2019). It can be explained that consumers are more likely to attempt and persist in behaviors they feel capable of performing. In addition, other factors related to individual differences are also shown in this stream. As proof, self-construal (Fan *et al.*, 2020), need for interaction (Amelia *et al.*, 2021), subjective norm (Fernandes and Oliveira, 2021; Moussawi and Koufaris, 2019), and prior experience and knowledge of technologies of relevance (Amelia *et al.*, 2021) facilitate service robot acceptance, while technology anxiety (Amelia *et al.*, 2021; Lee, Sheehan, *et al.*, 2021) and privacy risks (Jain *et al.*, 2022; Park *et al.*, 2021) hinder users from using service robots.

3.3 Relational components

In this research context, the relational dimension of user acceptance of robots highlights how users feel understood by and trust robots (Merkle, 2021). Trust and rapport have emerged as important relational factors in robot adoption research (Mele *et al.*, 2020). Note that rapport is defined as the personal

connection between a robot and a customer (Gremler and Gwinner, 2000; Wirtz *et al.*, 2018). Rapport is included as a relational resultant of robot anthropomorphism, which, in turn, affects the intention to use a robot (Blut *et al.*, 2021). Likewise, as a favorable perception in customer-robot interaction, rapport, together with trust, significantly impacts individual willingness to interact with robots (Mele *et al.*, 2020) and user acceptance of digital voice assistants (Fuentes-Moraleda *et al.*, 2020). Merkle (2021) suggested two relational components, i.e., benevolence and understanding, that determine robot acceptance. Note that benevolence often features as a part of trust (Danckwerts *et al.*, 2020; Wirtz *et al.*, 2018). Except for the two factors, the significance of user satisfaction is also underlined in robot acceptance (Stock and Merkle, 2017).

3.4 Exogenous factors

Apart from the three-dimensional components that contribute to customers accepting service robots, several critical factors are worth noting. Social influence — “*the extent to which consumers’ social networks believe they should use robots in service encounters*” (Lu *et al.*, 2019, p. 38) — significantly influence customer willingness to use AI devices (Chi *et al.*, 2022; Gursoy *et al.*, 2019; Ivkov *et al.*, 2020; Lin *et al.*, 2020) and customer acceptance of frontline service robots (Amelia *et al.*, 2021). Other task-/service-related factors have also been considered in the reviewed studies. As proof, service outcome (success vs. failure vs. failure with recovery) impacts usage intention through responsibility attribution (Mozafari *et al.*, 2021). Prior performance of robots also matters in service robot adoption; service context, whether the prior delivered *r*-service was satisfying, moderates the effect of personal innovativeness on perceived risk, thereby decreasing revisit intention in hotels (Lin *et al.*, 2021). Past studies also discuss service heterogeneity (Lin *et al.*, 2021) and task complexity (Amelia *et al.*, 2021).

4 Conclusion, implications, and limitations

With the rapid advance and implementation of AI robots, discussions on how robots will replace human labor have been omnipresent among academy and public media in recent years (Kim *et al.*, 2021). Presently, the development and deployment of service robots have not far reached the maximum potential yet, neither has the exploration of service robot adoption. This paper offers a conceptual framework that helps with a comprehensive and in-depth understanding of the drivers and obstacles of accepting service robots in the current literature. From the standpoint of triangulation perspectives with technology user, consumer, and interactor (Pedersen *et al.*, 2002), this paper structures the fundamental determinants in the reviewed studies from views of TAM, service quality, and expectancy-value theory, supplemented by antecedents of three main dimensions (i.e., robot-design, consumer-orientated, and relational components) and several exogenous factors.

This paper gives several preliminary insights for future studies regarding service robot adoption. First, this work is among the first, to our knowledge, to build a comprehensive framework by integrating the current knowledge of service robot adoption. By doing so, this study contributes to elaborating on and promoting the current situation regarding service robot adoption research. This framework can be viewed as a prototype in service robot adoption research. It would be interesting to investigate the weights of different factors in future studies to determine which ones exert the most significant impact on customer attitude towards robots and behavioral intention. The answer may not be of utter generalization that can apply universally because of situational differences like service industries and robot types. Still, it promises the potential to establish service industry-/robot type-orientated conceptual frameworks.

Second, our study indicates that multidimensions should be taken into account when discussing customer adoption of service robots. This paper further underpins the significance of the utilitarian value of using service robots to deliver customer service, not only involving perceived usefulness and ease of use but also related to performance expectancy and effort expectancy. In line with the argument by Li and Wang (2021) that service robots and customers both play roles of importance in customer satisfaction, this paper suggests that customers act in multiple roles in human-robot interaction. It highlights that not only the functionalities of robots matter but also social-emotional

elements play an essential part in service robot adoption. In this line, it is also necessary to understand the effects of customers' physical and psychological evaluation about the service robots, such as psychological comfort with robots.

Third, alongside the most presented robot-design components described in this paper, several constructs remain to be further investigated. As past studies indicated, "baby schema" features of robots can create cuteness perception (Murphy et al., 2019) and avoid the uncanny valley effect (Lv, Luo, et al., 2022). Cuteness design is significant in facilitating people accepting robots (Lv, Luo, et al., 2022) and expanding consumer tolerance of service failure (Lv et al., 2021). Echoing Blut *et al.* (2021), future research would turn to the design strategy pertaining to the level of cuteness for robots to endear robots to customers and generate affective bonds. Furthermore, considering the wide variety of services accomplished by service robots (Gursoy et al., 2019), how to pair robot-design features to service tasks deserves more attention to promote customer adoption of robots (Lv, Luo, et al., 2022).

The proposed conceptual framework is highly relevant to business practitioners designing/deploying service robots. First, this framework allows these practitioners to evaluate the factors that may typically attract customers to adopt *r*-services. Gaining knowledge regarding facilitators and barriers to using service robots is central to business managers' decision-making to increase customer satisfaction and loyalty. Second, given the fact that service robots are deployed to deliver customer service as a replacement for regular employees, customer attitudes toward service robots and behavioral intention to use service robots are not only strongly impacted by utilitarian aspects but also determined by the hedonic factor of perceived enjoyment (Guan et al., 2021). Thus, the hedonic value of using service robots should also be paid more attention to. Next to this, this paper also underlines the importance of perceived personalization, which can be underpinned in customized service performance. Combining with the roles of personal attributes in service robot adoption, this paper conveys the idea that all customers should not be treated alike. Fourth, trust has been emphasized not only as an antecedent but also as a resultant in service robot acceptance models (see, e.g., Lv, Yang, *et al.*, 2022; Mele *et al.*, 2020). Therefore, trust-building interventions, concerning, e.g., privacy protection and risk reduction, should attract enough attention from business practitioners to foster customer engagement in the trust-related robot using behavior. Finally, given the inevitableness of *r*-service failure at the current stage, it is necessary to consider remedial actions of a service failure with recovery. In this vein, the induced negative perceptions by service failures could be mitigated, to a large degree, to avoid hindering customers from reusing service robots.

This work has several limitations. First, a conceptual framework covering all constructs that foster customers to accept service robots is set up. The established framework is based on an integration of findings from various studies as regards particularly AI-enabled technology acceptance and customer perceptions and response to *r*-service. However, it can always happen that not all factors that affect customer intention to use service robots/robotic applications or visit *r*-service are covered in the current literature or are coped with by other work. Still, we can confidently claim that the proposed framework offers a coherent overview of most factors of high relevance under this circumstance. Second, just with any conceptual work, the present study is developed around a conceptual framework that stems from literature analysis, the entirety of which leaves to be verified empirically. Therefore, more empirical evidence in future studies to address this issue is encouraged.

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