Article:

Yoganathan, V. orcid.org/0000-0002-9285-4702, Osburg, V.-S., Kunz, W.H. et al. (1 more author) (2021) Check-in at the Robo-desk: Effects of automated social presence on social cognition and service implications. Tourism Management, 85. 104309. ISSN 0261-5177

https://doi.org/10.1016/j.tourman.2021.104309

Check-in at the Robo-desk: Effects of Automated Social Presence on Social Cognition and Service Implications

Abstract

The accelerated deployment of humanoid robots in hospitality services precipitates the need to understand related consumer reactions. Four scenario-based experiments, building on social presence and social cognition theories, examine how humanoid robots (vs. self-service machines) shape consumer service perceptions and intentions *vis-à-vis* concurrent presence/absence of human staff. The influence of consumers' need for human interaction and technology readiness is also examined. We find that anthropomorphizing service robots positively affects expected service quality, first-visit intention, and willingness to pay, as well as increasing warmth/competence inferences. These effects, however, are contingent on the absence of human frontline staff, which can be understood by viewing anthropomorphism as a relative concept. Humanoid robots also increase psychological risk, but this poses no threat to expected service quality when consumers' need for human interaction is controlled for. Hence, humanoid robots can be a differentiating factor if higher service quality expectations are satisfied. Additionally, we show that a humanoid robot's effect on expected service quality is positive for all but low levels of technology readiness. Further implications for theory/practice are discussed.

INTRODUCTION

Humanoid service robots have been described as "the most dramatic evolution in the service realm" (Mende et al., 2019, p. 535), especially as they are significantly different from previous service technologies owing to more human-like interactions. The ongoing COVID-19 crisis has further increased the propensity for robotic automation of frontline hospitality services of (Li et al., 2019; Park, 2020). However, differences in the perceptions and cognition of consumers in relation to emergent (e.g., humanoid service robot), as opposed to conventional (e.g., self-service machine), service technologies are not well-understood. Further, when a service is delivered in collaboration, understanding the role of human frontline employees in how consumers perceive such new technologies is also important (van Doorn et al., 2017). We therefore examine how humanoid service robots, in contrast to typical self-service machines, shape consumer cognition and service perceptions *vis-à-vis* the concurrent presence/absence of human frontline staff. We also consider the role that consumer characteristics play in this context, specifically, consumers' underlying need for human interaction in service scenarios, and their level of technology readiness.

Following Wirtz et al. (2018), service robots are defined as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (p. 909). Whereas service robots can be differentiated based on various characteristics, their level of anthropomorphism (i.e., humanoid vs. non-humanoid features) can be regarded as a critical factor that influences adoption, service quality, and service experience (Murphy et al., 2019; Xiao and Kumar, 2021). In the presence of such features, consumers perceive the service robot as another social entity because the robot manifests what is referred to as *automated social presence* (ASP) (Heerink et al., 2010; van Doorn et al., 2017). While there is now a steadily emerging stream of literature on service robots, empirical analysis of the effects of ASP in relation to consumer service outcomes remains scarce.

It must also be considered that robots and human staff can deliver services in collaboration. The interaction between ASP and *human social presence* (HSP) in a service scenario is expected to influence consumer service outcomes differently; for instance, service robots may substitute (replace human frontline staff) or augment (assist human frontline staff), which correspondingly shapes consumer service perceptions and experience (Larivière et al., 2017; van Doorn et al., 2017). In this context, it is unclear to what extent and how the anthropomorphizing of the service robot matters to consumers. As such, there remains a gap for advancing our knowledge of consumer service perceptions in service scenarios that result in the concurrence of ASP (e.g., induced by humanoid robots) and HSP (due to human staff involvement).

In this paper, we build on the theoretical underpinnings of social cognition, which help identify consumers' positive (warmth and competence) and negative (psychological risk and performance ambiguity) cognitive evaluations in relation to the ASP of humanoid service robots. Since social cognition ultimately shapes behavioral outcomes (Fiske et al., 2007), we investigate how humanoid service robots influence consumers' intention to visit and willingness to pay, as well as expected service quality, for a hospitality service provider that utilizes humanoid robots for frontline service tasks. In addition, we examine the extent to which social cognition effects are contingent upon consumer characteristics and preferences, namely, need for interaction with human service staff and technology readiness. To our knowledge, this is the first empirical attempt that considers these consumer-related aspects in relation to service robots, especially technology readiness, which has been widely discussed in relation to traditional self-service technologies (e.g., Blut and Wang, 2020).

In summary, through a series of scenario-based experimental studies, we contribute to service research in four main areas. First, we highlight that humanoid service robots can positively influence central consumer outcomes: expected service quality, visit intention, and willingness to pay (WTP). Second, we show how humanoid robots are a better alternative to self-service machines with reference to consumer cognitive evaluations (e.g., warmth and competence inferences). Third, we consider implications of humanoid robots delivering frontline service with the concurrent presence of human service staff. Finally, we illustrate the role of consumers' need for interaction with human staff and technology readiness in shaping the effect of humanoid robots on consumer service outcomes.

CONCEPTUAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Automated and Human Social Presence in Services

Automated social presence (ASP) describes the degree to which consumers perceive a machine as another social entity (Heerink et al., 2010). Whereas earlier versions of embodied artificial intelligence are considered to be primarily mechanical in form, the latest models of robots incorporate more humanlike features including empathy-simulation (Huang and Rust, 2018). As such, modern humanoid robots are able to manifest high ASP. This opens new opportunities for technology-enabled services, and further prospects for social engagement with consumers (van Doorn et al., 2017). While consumer transactions with standard cash machines or any other self-service technology are severely limited in comparison to human-to-human interactions, service technologies with a high degree of ASP can mimic aspects of human interactions. Smart speakers such as Amazon Echo simulate human-to-human communication, and therefore create the feeling of social presence. Likewise, there are humanoid service robots that reflect human characteristics, not least in their appearance (Wirtz et al., 2018). Hence, in line with extant literature on the topic, we consider service scenarios involving humanoid robots to induce high ASP in comparison to those involving conventional self-service machines, which induce low ASP.

An overview of previous research indicates that companies can expect a range of beneficial consumer-related outcomes for high as opposed to low ASP (Davenport et al., 2020; Kim et al., 2019). Consumers tend to favor robots that reflect human characteristics through mimicking their emotions and behaviors (Tielman et al., 2014). However, following the uncanny valley hypothesis (Mori, 1970), high levels of ASP (e.g., due to anthropomorphic features of service robots) can increase consumer trust and ultimately adoption behavior, so long as the machine does not appear too humanlike (Kim et al., 2019; Wirtz et al., 2018). Humanoid service robots can also induce compensatory responses such as buying status goods or over-ordering food (Mende et al., 2019).

In this paper, we explore consumer willingness to pay (WTP) and first visit intention in relation to humanoid service robots. As high levels of ASP lead to favorable consumer responses (Davenport et al., 2020; van Doorn et al. 2017) we expect that high ASP (e.g., humanoid service robot) may also increase consumer WTP. Similarly, we expect a positive effect on consumer's visit intention, given that anthropomorphic features such as empathy affect tourists' adoption behavior (de Kervenoael et al., 2020), which can ultimately be linked to visit behavior.

In addition, high levels of ASP have been associated with higher consumer expectations. For instance, consumers may expect a humanoid service robot to perform more like a human employee and deliver the same level of service quality, whereas expectations may be significantly lower when a consumer is faced with a traditional self-service machine (Duffy, 2003; Ho et al., 2020). This would ultimately mean that ASP indirectly influences consumer behavior, as the link between service quality expectations and consumption intention is well-documented in existing literature (e.g., Barrutia and Gilsanz, 2012; Dabholkar, 1996; Reimann et al., 2008). Moreover, Hui et al. (2004) highlighted the importance of vantage vs. qualifying attributes of services in relation to consumer satisfaction. The qualifying attributes (e.g., service quality) are essential for ensuring consumer satisfaction, upon which the influence of vantage attributes (i.e., those that help differentiate against competitors) is contingent. If humanoid service robots can be assumed to be a point of differentiation (i.e., vantage factor), then consumers would expect satisfactory service quality as a basic criterion for deciding to visit or pay for a robot-service provider (e.g., a robot hotel). Consequently, we expect the high level of ASP induced by a humanoid robot to increase consumers' service expectations, which subsequently affect outcomes such as consumers' visit intention and WTP.

Hypothesis 1: A humanoid robot (vs. self-service machine) increases expected service quality (H1a) and thus, indirectly increases consumer visit intention (H1b) and WTP (H1c) via expected service quality.

Generally, the implementation of humanoid robots needs to be considered in conjunction with the role of human staff, because technology can either act as a substitution, or an assistance for human staff to facilitate service interactions (Lariviere et al., 2017; Mende et al., 2019). For instance, travelers can use baggage drop-off kiosks at an airport with (i.e., assistance) or without (i.e., substitution) the support of human staff. Based on this assumption, van Doorn et al. (2017) introduce a 2x2 matrix of technology in service experiences, which considers the degree of ASP in relation to HSP. The consideration of how ASP and HSP interact is important because these two forms of social presence are distinct. Service robots, for example, differ from frontline employees in that they are likely to shape consumer experiences in a manner that is characterized by a homogenous service delivery, reduced biases, but also limited creative problem solving and out-of-box thinking (Wirtz et al., 2018). It therefore makes a fundamental difference whether consumers encounter service robots with or without the concurrent presence of human frontline staff (Mende et al., 2019).

Touré-Tillery and McGill (2015) indicate that consumers may perceive anthropomorphism as beneficial when comparing between high and low levels of ASP whereas when contrasting anthropomorphized machines (e.g., humanoid robot) with humans, anthropomorphism appears less human, as the non-human characteristics become more salient. For example, consumers may perceive a humanoid service robot (high ASP) as more favorable when it is compared with a self-service machine (low ASP) instead of frontline human employees. Whereas contexts may exist in which a collaborative service provision by ASP and HSP may be beneficial (e.g., elderly care) (van Doorn et al., 2017), the salience of interacting with a robot should be higher in the presence of HSP, ultimately affecting consumer perceptions. This can be explained by the three-factor theory of anthropomorphism (Epley et al., 2007), according to which anthropomorphism is more successful when individuals feel a lack of interactions with other humans, which is given in the context of low HSP. Thus, we propose that the positive effects of humanoid robots (high ASP) on expected service quality, visit intention and WTP will diminish once HSP is introduced.

Hypothesis 2: Human social presence moderates (either reduces or negates) the direct effect of high (vs. low) ASP on expected service quality (H2a) and indirect effects of high (vs. low) ASP on consumer visit intention (H2b) and willingness to pay (H2c) via expected service quality.

Positive Cognitive Evaluation: Warmth and Competence

The degree of ASP and HSP does not only influence consumer service outcomes directly, but also indirectly via consumer evaluations based upon social cognition effects (van Doorn et al., 2017). As a positive form of cognitive evaluation, social cognition consists of two dimensions, namely, warmth and competence perceptions, which summarize how individuals characterize each other (Fiske et al., 2007). Specifically, from an evolutionary perspective, an encounter with conspecifics results in an evaluation of the other’s intent of good or ill (i.e., warmth), and their capability of pursuing intended actions (i.e., competence) (Fiske et al., 2007). It has been shown that warmth and competence inferences are relevant in determining consumer behavioral intentions (Scott et al., 2013). The general assumptions of social cognition can also be applied to non-human entities, such as robots, especially as artificial intelligence applications become increasingly humanlike, thus creating high levels of social presence (Jörling et al., 2019; Lee et al., 2006). Therefore, service technologies can also be assessed in relation to their warmth, which captures "perceived intent, including friendliness, helpfulness, sincerity, trustworthiness and morality" as well as competence, which describes "perceived ability, including intelligence, skill, creativity and efficacy" (Fiske et al., 2007, p. 77).

Consumers may generally perceive service technology as less empathetic when it does not show human-like characteristics, which ultimately affects adoption intention (Davenport et al., 2020). The anthropomorphic characteristics of a service technology may, therefore, influence the fulfilment of consumers' social and relational needs (Wirtz et al., 2018). For instance, a humanoid service robot is likely to be perceived as friendlier, more helpful, and trustworthy compared with a self-service machine due to the human touch of the consumer-service robot interaction.

Due to humanlike characteristics, consumers tend to perceive that the technology is more capable (Davenport et al., 2020). For example, service robots are generally expected to be reliable with respect to functional tasks, i.e., they perform well, without serious errors (Huang and Rust, 2018). This is an important point of differentiation compared to a typical self-service machine, which is usually perceived as less competent, and consequently, has a longer adoption phase (Wirtz et al., 2018). This could be because consumer interactions with service robots tend to be similar to those with human staff in terms of consumer expectations, compared to traditional self-service technology (Ho et al., 2020). Consequently, a high level of ASP should not only increase warmth, but also competence perceptions.

The two dimensions of social cognition ultimately influence a range of outcomes because if an individual is perceived as warm and competent, he/she receives positive responses, whereas the opposite perceptions lead to negative responses (Fiske et al., 2007). Previous work illustrates that warmth and competence perceptions are influential in buyer-seller relationships, and ultimately in shaping consumer behavioral intentions (Scott et al., 2013). It has also been discussed that a physical service robot has the potential to shape consumer expectations and positively influence consumer experience (van Doorn et al., 2017; Wirtz et al., 2018). For example, consumers may perceive it as more appealing and professional if they are greeted at a shop entrance by a humanoid service robot as opposed to a voice-based smart assistant, which ultimately increases their service expectations. Empirical investigations into actual interactions between humans and humanoid robots have also demonstrated that such robots can indeed influence social interactions by manifesting a personality and social presence (Horstmann et al., 2018; Lee at al., 2006). In addition, anthropomorphized communications in the tourism context are found to increase visit intention via social-cognitive evaluations such as warmth inferences (Lee and Oh, 2020). We therefore predict that humanoid robots will have a positive influence on both dimensions of social cognition, which in turn increases service quality expectations.

Hypothesis 3: A humanoid robot (vs. self-service machine) increases consumers' warmth (H3a) and competence (H3b) perceptions, and therefore indirectly increases expected service quality via warmth (H3c) and competence (H3d).

Nonetheless, the advantages of high levels of ASP may decrease in the concurrent presentation of HSP (Touré-Tillery and McGill, 2015), as already discussed in relation to Hypothesis 2. The interaction of frontline human staff and a service robot in a service encounter may make the non-human characteristics of the robot more salient, thus reducing social cognition perceptions. Actual differences between robots and humans may become more evident when both are present together, thereby attenuating the perceived anthropomorphism of a machine and its ensuing effects (*ibid*).

Hypothesis 4: Human social presence moderates (reduces or negates) a humanoid robot's (vs. self-service machine's) direct effects on warmth (H4a) and competence (H4b) perceptions and indirect effects on expected service quality via warmth (H4c) and competence (H4d).

Negative Cognitive Evaluation: Psychological Risk and Performance Ambiguity

Mick and Fournier (1998) presciently identified that technology's influence on users can be paradoxical, simultaneously leading to desirable and undesirable consequences (e.g., technology makes some aspects of life easier and others more difficult, gives us freedom but also enslaves us to self-serving routines). Introducing robots to the service context is not a straightforward process and its adoption depends on various factors (Xiao and Kumar, 2021). Thus, negative connotations should also be considered when exploring consumers' perceptions of robots in the service context (Huang and Rust, 2018; Wirtz et al., 2018). For example, previous work has focused on threats to human jobs (Huang and Rust, 2018; McLeay et al., 2021), responsibility perceptions (Jörling et al., 2019), and compensatory consumption (Mende et al., 2019). An exploration of negative evaluations is not only pertinent from a technological viewpoint, but also in relation to social cognition (Fiske et al., 2007).

As negative technology-related equivalents of warmth and competence, we examine psychological risk and performance ambiguity. Both have been identified as essential aspects of consumers' evaluation of service technology (Huang and Rust, 2017; Johnson et al., 2008; Stone and Grønhaug, 1993). Psychological risk relates to the quality of a consumer's interaction with others, or in the present context, the technology (Jacoby and Kaplan, 1972; Stone and Grønhaug, 1993). Thus, it reflects the antithesis of the warmth dimension of consumers' cognitive evaluations. Performance ambiguity describes the way in which consumers are often not able to confidently assess the performance reliability of a service technology (Johnson et al., 2008) hence, representing the competence dimension.

In the service context, psychological risk is related to the extent to which a consumer feels uncomfortable, anxious, or tense when interacting with a specific technology or device (Stone and Grønhaug, 1993). For example, in relation to service robots, consumers may have concerns about data privacy and unethical use of data (Davenport et al., 2020; van Doorn et al., 2017). Nonetheless, anthropomorphic characteristics may reassure consumers and decrease risk perceptions (Touré-Tillery and McGill, 2015). We therefore predict that high ASP reduces consumers' perceived psychological risk.

Performance ambiguity is another critical dimension, because service consumers want to "perceive control over the technology rather than to feel controlled by it" (Jörling et al., 2019, p. 14). Wirtz et al. (2018) argue that service robots are superior to self-service machines when it comes to service failures and consumer errors. Technologies that enable relationship building, such as humanoid service robots, are likely to reduce performance ambiguity because they facilitate smoother transactions and trust in their performance (Huang and Rust, 2017; Verma et al., 2016). Technological barriers also tend to be lower in human(-like) interaction, which reduces consumers' perceived responsibility and increases their perceived control (Schaarschmidt and Höber, 2017). Thus, we expect that high ASP reduces consumers' performance ambiguity.

In addition, performance ambiguity has been negatively linked to consumer-related outcomes, such as technology adoption, purchase behavior and consumer satisfaction (Collier and Kimes, 2012; Huang and Rust, 2017; Johnson et al., 2008). Psychological risk has similarly been discussed as affecting consumer behavior and expectations negatively (Davenport et al., 2020). This is supported by the general assumption that the social cognition dimensions affect a range of (consumer-related) outcomes (Fiske et al., 2007). Thus, we expect that high levels of ASP increase service quality expectations through reduced psychological risk and performance ambiguity perceptions.

> **Hypothesis 5:** A humanoid robot (vs. self-service machine) decreases consumers' psychological risk (H5a) and performance ambiguity (H5b) therefore, indirectly increases expected service quality via psychological risk (H5c) and performance ambiguity (H5d).

Consumer Need for Human Interaction and Negative Cognitive Evaluation of ASP

Generally, technology adoption does not only depend on characteristics of the technology, but also the consumers' characteristics and preferences (Blut and Wang, 2020; Xiao and Kumar, 2021). Hence, it is important to consider the extent to which consumers' cognitive evaluation of ASP differs in relation to their characteristics or preferences. Social cognition is influenced by characteristics and preferences of the individual (e.g., demographics, traits) who conducts the evaluation (Fiske et al., 2007). Similarly, consumer preferences are likely to moderate the influence that technological features (e.g., anthropomorphism, autonomy) have on outcomes such as service quality and service experience (Xiao and Kumar, 2021).

In the context of service technology, consumers' need for interaction with service employees (NISE) is considered as a general disposition describing a consumer's desire to engage with humans in a service situation (Dabholkar, 1996). NISE is an important factor, since it represents one of the core inhibitors of service technology adoption (Collier and Kimes, 2012; Oh et al., 2013). It is particularly crucial for contexts where service technology replaces frontline human staff (McLeay et al., 2021; Schaarschmidt and Höber, 2017). If service robots are superior to self-service machines, it then remains to be ascertained whether NISE is as influential a factor in relation to consumer perceptions and cognitions of service robots compared to traditional self-service technology.

In service scenarios involving self-service technologies, if the performance of the technology is satisfactory to consumer preferences and expectations (e.g., it is fast and accurate), then consumers are less likely to need, and therefore seek, the assistance of human service staff (Collier and Kimes, 2012; Oh et al., 2013). Hence, the features of self-service machines (such as speed and accuracy) directly or indirectly will influence consumers' NISE in specific service situations. However, consumers also possess a general tendency for seeking interactions with human staff, independent of the service scenario, in which case, NISE can function as a moderator between features of the technology and consumer evaluations (Schaarschmidt and Höber, 2017). As such, consumers with high NISE may tend to be less inclined towards service technology, whereas consumers with low NISE are more in favor (Oh et al., 2013). Therefore, any negative perception with regards to humanoid robots, such as risk and ambiguity, is likely to be increased in consumers with high NISE, and correspondingly in consumers with low NISE such negative perceptions are likely to be reduced.

Hypothesis 6: Consumers' need for interaction with service employees (NISE) moderates (increases) a humanoid robot's (vs. self-service machine's) direct effects on psychological risk (H6a) and performance ambiguity (H6b) and therefore, also increases the indirect effects on expected service quality via psychological risk (H6c) and performance ambiguity (H6d).

The Role of Consumer Technology Readiness

Consumers' readiness to use new technologies has been shown to influence a range of consumer-related outcomes, including their cognitive evaluations of service technologies (Blut and Wang, 2020). For example, technology readiness has been identified as a key influence on consumer adoption of self-service machines (Ferreira et al., 2014; Meuter et al., 2005). Further, research shows that consumers' technology readiness moderates the influence of the perceived quality of service technologies on consumer satisfaction (Wang et al., 2017). Nevertheless, not much is empirically known about how technology readiness influences consumers' social cognition in relation to ASP, especially where robots are concerned. An understanding of how varying levels of technology readiness affects the evaluation of ASP can, therefore, provide further insights into the adoption of humanoid service robots. As proposed by van Doorn et al. (2017), consumers with high technology readiness are more likely to be positively influenced by humanoid service robots, because such consumers are more favorably disposed towards new technology in general. Therefore, a humanoid service robot is more likely to have a positive influence on expected service quality and visit intention for consumers with high technology readiness.

Hypothesis 7: A humanoid robot (vs. self-service machine) has a positive effect on expected service quality (H7a) and visit intention (H7b) for consumers with high technology readiness.

Figure 1 summarizes our conceptual framework, which is tested in four studies. Study 1 investigates the comparative effects of the ASP induced by humanoid robots on central consumer outcomes (i.e., expected service quality, visit intention, and WTP) as well as the impact of the presence of human staff (i.e., HSP). Study 2 focuses on the warmth and competence perceptions of humanoid robots, along with concurrent presence (or absence) of human staff. Study 3 investigates humanoid robots' effect on psychological risk and performance ambiguity while accounting for consumers' need for interaction with human staff. Finally, Study 4 examines differences in humanoid robots' influence on expected service quality and visit intention based on consumers' technology readiness.

INSERT FIGURE 1 ABOUT HERE

STUDY 1: ASP AND CONSUMER SERVICE OUTCOMES

Study 1 tests the general influence of ASP and HSP on consumer service expectations and consumer-related outcomes. Specifically, we explore how high (represented by humanoid service robot) and low (represented by self-service machine) levels of ASP influence service expectations, visit intention, and consumers' WTP. We also consider potential interactions with HSP, i.e., whether ASP substitutes or complements frontline service employees. The chosen service scenario is grounded in the travel context because service robots and the anthropomorphizing of service technology in general, are becoming particularly important for travel and hospitality services (Murphy et al., 2019).

Method

Procedure. 300 randomly sampled European consumers, who regularly travel for leisure, were recruited by a professional market research company (PCP Ltd) that specializes in representative consumer samples. The market research firm has a registered panel of consumers across age range, gender, and other demographics, to which the firm administers the survey via their proprietary online portal. Sample sizes were determined in advance to allow for sufficient power (n>30 per cell) and once the data collection commenced, all responses were recorded until reaching or exceeding the required sample size. In a 2x2 between-subject online experiment, automated [high (n=150), low (n=150)] and human [(high (n=150), low (n=150)] social presences were manipulated based on van Doorn et al.'s (2017) framework, according to which a humanoid service robot and a self-service machine represented high and low levels of ASP respectively.

At the beginning of the study, participants were asked to imagine that, while traveling for leisure, they have just arrived at their hotel and wish to check in. Respondents were further informed that the check-in process is automated. They were then randomly assigned to one of the experimental conditions and provided with a detailed description of their allocated check-in scenario. In addition to the degree of automated social presence (high: humanoid service robot, low: self-service machine), the descriptions specified whether human staff are present or absent. The descriptions were supplemented by an image, which, depending on the assigned condition, showed a reception desk with a humanoid robot or a self-service machine. Appendix B provides detailed descriptions of all check-in scenarios. The scenarios were pre-tested using an MTurk panel of 50 respondents prior to being used in the main study.

Measures. The scales and items for all four studies are listed in Appendix C. Variables were measured on a 7-point scale, except where original scales differed from this, or another approach was more appropriate (e.g., willingness to pay). In Study 1, Expected Service Quality was measured with a three-item scale from Dabholkar (1996) [Composite Reliability (CR) = 0.93; Average Variance Extracted (AVE) = 0.83]. Visit Intention was measured using an item adopted from Choi et al. (2018), which was originally developed by Zeithaml et al. (1996). WTP was assessed through a sliding scale, whereby respondents were asked to indicate the amount they would be willing to spend in addition to or less than the specified average rate per night by using the slider. The manipulation check involves respondents being presented with the 7-point social presence scale from Lee at al. (2006) following the experimental scenarios for all conditions ($mean_{humanoid\_robot}$ = 5.59; p=0.01). Similarly, for the realism check, the respondents were presented with a scale from Dabholkar (1996) following the experimental scenarios. However, in this case, a statistical difference between conditions is inapplicable, as all conditions are of relevance (as opposed to their being a difference); mean scores: m_1=4.9, m_2=4.7, m_3=4.8, m_4=4.7.

Results

Assumption checks were conducted as follows. Multicollinearity was assessed using variance inflation factors (VIF): expected service quality=2.49, visit intention=2.23, and WTP=1.21. Multivariate normality was established using Doornik and Hansen's (2008) omnibus test (χ^2/df=5.99/6; p=0.42); in addition, the Central Limit Theorem applies in each category of experimental conditions (n>30). Homogeneity of covariance matrices is established using Box's M test (χ^2/df=20.62/18; p=0.30).

Preliminary analysis using a two-way factorial MANOVA shows that a humanoid robot (vs. self-service machine) has significant main effects on expected service quality (*F*=22.2; df=1; p=0.000; $\eta^2_{partial}$=0.07), visit intention (*F*=7.5; df=1; p=0.007; $\eta^2_{partial}$=0.03) and WTP (*F*=6.8; df=1; p=0.009; $\eta^2_{partial}$=0.02), as well as interaction effects with HSP on expected service quality (*F*=5.3; df=1; p=0.022; $\eta^2_{partial}$=0.02) and visit intention (*F*=6.8; df=1; p=0.010; $\eta^2_{partial}$=0.02), but not on WTP (*F*=0.61; df=1; p=0.436; $\eta^2_{partial}$=0.00). Hence, H1a is supported. Figure 2 presents a comparison of mean values by condition.

Further analysis was conducted using Hayes' (2018) PROCESS tool (model 8); bias-corrected confidence intervals (CI) and robust standard errors were computed by using bootstrapping (N=5000). Results show that a humanoid robot (vs. self-service machine) has a positive indirect effect on visit intention and WTP via expected service quality. Hence, H1b and H1c are also supported. In addition, HSP negatively moderates the direct effect of a humanoid robot on expected service quality (β=-0.19; p=0.02; Figure 3); thus, H2a is supported. Further, a humanoid robot's indirect effects on visit intention (β=0.48; CI: 0.30, 0.68) and WTP (β=2.27; CI: 0.92, 3.95) are only significant when HSP is low; thus, H2b and H2c are also supported. An overview of statistical results is presented in Table 1.

INSERT FIGURES 2 AND 3 ABOUT HERE

INSERT TABLE 1 ABOUT HERE

In sum, these results provide a basic understanding of the effects of humanoid service robots (i.e., high ASP) and highlight that these are contingent on human social presence (HSP). When HSP is low (no frontline service staff), a humanoid robot has a positive effect on consumer visit intention and WTP by increasing expected service quality. Having frontline service staff alongside the humanoid robot reduces the robot's effect on expected service quality and thus negates its positive impact on visit intention and WTP.

STUDY 2: POSITIVE COGNITIVE EVALUATIONS OF ASP

This study extends the exploration of ASP and HSP's influence on consumer service outcomes by focusing on social cognition. Specifically, we explore how warmth and competence perceptions can differ between high and low levels of ASP and HSP. Further, we link social cognition to consumers' service expectations.

Method

Procedure. A random sample of 334 responses was collected using the same sampling and data collection procedure as in Study 1. We again followed a 2x2 between-subject design, manipulating both ASP [high (n=166), low (n=168)] and HSP [high (n=182), low (n=152)] following the stimuli and procedure applied in Study 1.

Measures. To better understand the differences in service quality perceptions depending on levels of ASP and HSP, both the warmth and competence dimensions of social cognition were measured according to Scott et al. (2013). Specifically, three items each assessed respondents' perceptions of Competence (e.g., "incompetent/competent") [CR = 0.94; AVE = 0.84] and Warmth (e.g., "uncaring/caring") [CR = 0.83; AVE = 0.71]. Expected Service Quality was measured the same way as in Study 1 [CR = 0.93; AVE = 0.82]. Manipulation and realism checks also followed the same procedure as before; manipulation checks: ASP (m=5.56; p=0.01) and HSP (m=5.68; p=0.01); realism scores for each condition: m_1=4.8, m_2=4.7, m_3=4.5, m_4=4.4.

Results

Multicollinearity was assessed using VIF: expected service quality=2.06, warmth=3.31, and competence=3.30. Multivariate normality was established using Doornik and Hansen's (2008) omnibus test (χ^2/df=4.21/6; p=0.21); in addition, the Central Limit Theorem applies in each category of experimental conditions (n>30). Homogeneity of covariance matrices is established through Box's M test (χ^2/df=22.61/18; p=0.21).

A preliminary analysis using two-way factorial MANOVA shows that a humanoid robot (vs. self-service machine) has significant main effects on expected service quality (F=22.7; df=1; p=0.000; $\eta^2_{partial}$=0.07), warmth (F=17.27; df=1; p=0.000; $\eta^2_{partial}$=0.05) and competence (F=10.36; df=1; p=0.001; $\eta^2_{partial}$=0.03), as well as interaction effects with HSP: expected service quality (F=5.1; df=1; p=0.025; $\eta^2_{partial}$=0.02) warmth (F=10.7; df=1; p=0.001; $\eta^2_{partial}$=0.03) and competence (F=12.6; df=1; p=0.000; $\eta^2_{partial}$=0.04). Figure 4 presents a comparison of mean values by condition. The main hypothesis testing procedure applied PROCESS (model 8) as before with robust standard errors with bootstrapping (N=5000), which confirmed that a humanoid robot (vs. self-service machine) increases warmth and competence perceptions and thus, has an indirect effect on expected service quality via warmth and competence. Hence, H3a-H3d are supported. Furthermore, HSP negatively moderates the direct effect of a humanoid robot (vs. self-service machine) on warmth (β=-0.49; p=0.00; Figure 5) and competence (β=-0.57; p=0.00; Figure 6); therefore, H4a and H4b are supported.

INSERT FIGURES 4, 5, AND 6 ABOUT HERE

In addition, a humanoid robot's (vs. self-service machine's) indirect effects on expected service quality via warmth (β=0.39; CI: 0.18, 0.63) and competence (β=0.41; CI: 0.20, 0.68) are only significant when HSP is low; therefore, H4c and H4d are also supported. An overview of results is presented in Table 2.

INSERT TABLE 2 ABOUT HERE

The results help understand how humanoid service robots (i.e., high ASP) increase expected service quality: by increasing positive social cognitive evaluations (warmth and competence). However, corresponding to findings from Study 1, these effects are contingent on HSP. That is, the presence of human frontline staff alongside a humanoid robot negates the robot's effects on warmth and competence perceptions and therefore, indirectly on expected service quality.

STUDY 3: NEGATIVE COGNITIVE EVALUATIONS OF ASP

Whereas Study 2 examined consumers' positive cognitive evaluations of ASP, Study 3 explores potential negative social cognitions. We particularly investigate whether psychological risk and performance ambiguity perceptions differ between ASP levels. Furthermore, we consider how these effects may depend on consumers' Need for Interaction with Service Employees (NISE).

Method

Procedure. A random sample of 430 responses was collected following the same sampling and data collection procedure as in preceding studies using a market research firm. This study included ASP [high (n=213) and low (n=217)] as a between-subject factor, but HSP was kept constant (no human staff) across the conditions. In line with the previous studies, high ASP was embodied by a humanoid service robot, whereas low ASP was represented by a self-service machine.

At the start of the study, participants were asked to imagine that while traveling for leisure, they have arrived rather late at their hotel to check in. Given their late arrival, participants were told they could only check in through a fully automated process. At this stage, respondents were randomly assigned to one of the two experimental conditions. The scenario description specified the level of ASP and the nature of information respondents would need provide to the self-service machine/humanoid robot in order to check in. The latter was included to specify the interaction and information requirement. Specifically, the following description was provided for the condition of high ASP: "*As you arrived late, you can only check in with the robot that looks like a human. No human staff are available; the check-in process is fully automated. To successfully check in and get the electronic key card to your room, you need to provide your: i) booking details, and ii) credit card details for authorization*." For the condition of low ASP, the phrase "robot that looks like a human" was replaced by "self-service machine". In addition to the description, the experimental stimuli included an image of a reception desk with either a humanoid robot or self-service machine.

Measures. As in Studies 1 and 2, manipulation and realism checks were applied following the previously described procedure; the manipulation check for ASP was significant (m=5.52; p=0.01) and the realism scores were also high for each condition (m_1=5.1, m_2=5.4). Following the exposure to scenarios, we measured Performance Ambiguity with three items from Johnson et al. (2008) [CR = 0.89; AVE = 0.73], Psychological Risk with the 3-item scale of Stone and Grønhaug (1993) [CR = 0.95; AVE = 0.87] and NISE with a four-item scale by Dabholkar (1996) [CR = 0.72; AVE = 0.54]. Respondents indicated their agreement with the statements belonging to all three constructs on 7-point Likert-type scales. In addition, Expected Service Quality was measured in the same way as in Study 1 and 2 [CR = 0.85; AVE = 0.67].

Results

Multicollinearity was assessed using VIF: expected service quality=1.19, performance ambiguity=1.36, psychological risk=1.45, and NISE=1.09. Normality tests were not required, as bootstrapped (N=5000) standard errors and 95% bias-corrected confidence intervals were obtained as part of the hypothesis testing procedure using PROCESS (model 8). In addition, the Central Limit Theorem applies in each category of experimental conditions (n>30). Figure 7 presents a comparison of mean values by condition. Results confirm that a humanoid robot (vs. self-service machine) *increases* psychological risk (β=0.32; CI: 0.01, 0.62; $\eta^2_{partial}$=0.02) but has no significant effect on performance ambiguity (β=0.10; CI: -0.16, 0.36; $\eta^2_{partial}$=0.00); thus, both H5a and H5b are not supported. Further, a humanoid robot (vs. self-service machine) has a negative indirect effect on expected service quality via psychological risk (β=-0.26; CI: -0.35, -0.18); there is no indirect effect via performance ambiguity (β=--0.04; CI: -0.14, 0.07). Hence, H5c and H5d are not supported.

INSERT FIGURE 7 ABOUT HERE

NISE does not have any moderating influences on the direct effects of a humanoid robot (vs. self-service machine) on psychological risk (β=0.16; CI: -0.16, 0.47) or performance ambiguity (β=0.13; CI: -0.14, 0.39), so H6a and H6b are not supported. However, the indirect effect on expected service quality via psychological risk is *negated* by the inclusion of NISE in the model (for performance ambiguity, there is no indirect effect), since NISE's direct effect on psychological risk is nontrivial and significant (β=0.72; p=0.00). Thus, H6c and H6d are not supported. A summary of results is presented in Table 3.

INSERT TABLE 3 ABOUT HERE

The results advance our understanding in relation to humanoid service robots (i.e., high ASP) by highlighting the role of perceived psychological risk in determining expected quality of services provided by a humanoid robot. Contrary to expectations, a humanoid robot increases psychological risk (but has no effect on performance ambiguity), thus lowering expected service quality. However, when NISE is controlled for, the increase in psychological risk does not affect expected service quality. This finding provides further insight into the role of human staff involvement in automated frontline service scenarios, but at the same time helps differentiate between the positive and negative aspects of social cognitive evaluation. While positive aspects of humanoid service robots are prominent in the absence of human staff involvement, the ultimate impact of the increase in psychological risk on expected service quality is driven by consumers' underlying need for interaction with human service employees, irrespective of humanoid robot involvement.

STUDY 4: ASP AND CONSUMER TECHNOLOGY READINESS

Method

Procedure. A random sample of 577 travel consumers was collected following the same sampling and data collection procedure as before using the same market research firm. This study followed the same design as in Study 3, whereby ASP [high (n=298) and low (n=279)] was treated as a between-subject factor, but HSP was kept constant (no human staff). The same experimental stimuli/scenarios were used as in Study 3 and the procedure followed the previously documented steps, in which participants were instructed to imagine that they are using a fully automated check-in process upon their late arrival at the hotel. Participants were randomly assigned to the experimental conditions.

Measures. The manipulation and realism checks were applied as per the previously described procedure; the manipulation check for ASP was significant (m=5.19; p=0.00) and the realism scores were high for each condition (m_1=4.8, m_2=5.2). In addition to Visit Intention (Choi et al., 2018) and

Expected Service Quality (Dabholkar, 1996) [CR = 0.93; AVE = 0.82], the Technology Readiness Index 2.0© (Parasuraman and Colby, 2015) was measured on a 5-point Likert scale [CR = 0.82; AVE = 0.71].

Results

TRI was computed as prescribed by Parasuraman (2000), and analysis was conducted using PROCESS (model 8) as before. VIF: service quality=2.16, visit intention=2.21, and TRI=1.20. Normality tests were not required, as bootstrapped (N=5000) standard errors and 95% bias-corrected confidence intervals were obtained as part of the hypothesis testing procedure, and the Central Limit Theorem applies in each category of experimental conditions (n>30). The Johnson-Neyman procedure (Hayes, 2018) for identifying significance regions revealed that a humanoid robot's (vs. self-service machine's) effect on expected service quality is significant and positive for TRI values exceeding 2.1 (88.4% of distribution), i.e. a humanoid robot has a positive effect on expected service quality at average and high levels of TRI (Figure 8). Results therefore support H7a.

INSERT FIGURE 08 ABOUT HERE

As seen in Figure 9, a humanoid robot's (vs. self-service machine's) effect on visit intention is significant and *negative* for TRI values below 2.8 (35% of distribution). A second region of significance is found where a humanoid robot's (vs. self-service machine's) effect on visit intention is *positive* for TRI values exceeding 4.5; however, this is likely to reflect a niche consumer segment as it accounts only for a very small proportion of the sample (0.2%). Hence, a humanoid robot (vs. self-service machine) has a negative effect on visit intention for low TRI, and a positive effect for very high TRI. Therefore, results partially support H7b (effect is positive only for very high TRI).

INSERT FIGURE 09 ABOUT HERE

DISCUSSION

There is widespread agreement that the advent of robots in service frontlines will revolutionize the service world (Mende et al., 2019; Wirtz et al., 2018). Although theorists forecast the replacement of human frontline employees by robots in various areas (Huang and Rust, 2018; Susskind, 2020), provision of services through human-robot collaboration may still have its place in newer business models that are focused on creating superior consumption experience and consumer value (Davenport et al., 2020; Huang et al., 2019; Larivière et al., 2017). Moreover, it is unclear whether service robots will take over all tasks that are currently handled by self-service machines, since the extent of robot automation is contingent on complex interrelationships among a variety of factors pertaining to robot-human interactions (Xiao and Kumar, 2021). Consequently, an urgent need arises for the consideration of potential implications of joint human-robot service provision.

Against this backdrop, our research examines consumer reaction to humanoid service robots in comparison to conventional technologies such as self-service machines. A particular focus was on the presence or absence of human frontline staff during the service delivery as well as consumer preferences such as the need for interaction with human staff and technology readiness. Based on our research, several implications can be drawn for service research and practice, which we elaborate on next.

Theoretical Implications

Humanoid robots positively influence central consumer outcomes. In accordance with existing conceptual work (van Doorn et al., 2017; Wirtz et al., 2018), we verify the positive influence of humanoid service robots' high automated social presence on consumers' behavioral intentions through social-cognitive evaluations. While there is an increasing stream of research focusing on robot-delivered frontline services, there is limited empirical work that examines the role of humanoid robots in shaping consumer expectations regarding service quality. Our findings show that anthropomorphism in service robots directly influences service quality expectations and, thereby, consumers' visit intention and willingness to pay. Some previous empirical studies on frontline service robots have reported negative consumer outcomes, such as negative attitudes, feeling lack of responsibility, and unhealthy eating (Jörling et al., 2019; Kim et al., 2019; Mende et al., 2019). In contrast, our findings indicate that humanoid robots can lead to positive consumer intentions towards the service, though this comes with the understandable expectation that humanoid service robots on the frontline equate to increased service quality. As Duffy (2003) and Ho et al. (2020) have noted, consumers expect the performance of a robot with humanoid features to be comparable to human staff, which explains why humanoid robots give rise to greater service quality expectations compared to self-service machines. Further, our results indicate that the presence of humanoid robots in frontline service may well be a vantage factor (Hui et al., 2004), which is appreciated by consumers, provided service quality expectations are satisfactory (i.e., service quality in this respect is a qualifying factor). In addition, investigation of the social-cognitive evaluations (e.g., warmth and competence) through which these outcomes take effect, provides further insights on the use of humanoid service robots, especially as replacements for self-service machines.

Humanoid robots as replacement for self-service machines. The ability of humanoid robots to manifest a distinct presence and personality in social interactions has been observed in prior work (Horstmann et al., 2018; Lee at al., 2006). Accordingly, our research finds that consumers perceive greater warmth and competence in the service delivery where humanoid robots are involved, as opposed to self-service machines, which in turn contributes to higher expectations of service quality. This indicates that consumers appreciate the progress made in service technology from rather unsocial and monotonous self-service machines to more social and flexible humanoid service robots. The ability of machines to deliver warmth or to mimic what are generally perceived as being uniquely human capabilities in service encounters has not been a prominent focus of research on conventional self-service technology. Although Kim et al. (2019) found that anthropomorphism in robots leads to negative consumer attitude although increasing perceived warmth, we find that the warmth and competence perceptions induced by anthropomorphic features lead to a positive effect on expected service quality. Hence, while supporting observations from previous studies (e.g., de Kervenoael et al, 2020; Lee and Oh, 2020; Tielman et al., 2014), our findings also extend the understanding of the psychological impact of humanoid service robots. Overall, we find that humanoid robots can successfully replace traditional self-service machines by contributing warmth and competence to the service encounter, whereas the literature on service robots has focused more on the replacement of human staff in frontline service (e.g., Huang and Rust, 2018; Larivière et al., 2017).

Can robot warmth and competence match the human service touch? Prior conceptual works have called for more human-robot collaboration in service provision, such that robots augment the service provided by human staff (Lariviere et al. 2017; Wirtz et al., 2018; Xiao and Kumar, 2021). However, despite the advantages of humanoid service robots compared to self-service machines, we observed that the favorable impact of humanoid robots on service-related consumer intentions (e.g., WTP, first-visit intention) as well as perceived warmth and competence does not materialize when the service is delivered in the presence of a human employee. The reason for this lies in understanding anthropomorphism as a relative concept; when an anthropomorphic entity (e.g., humanoid robot) is compared to an inanimate object or a typical self-service machine, its human-like features are perceived favorably by us, but the opposite holds if the comparison is drawn between the anthropomorphic entity and a real human (Epley et al., 2007; Touré-Tillery and McGill, 2015). From another perspective, recent research suggests that consumers may not necessarily perceive a difference between robot and human provided services because they expect both to represent the service provider alike and to have the same role in service delivery (Ho et al., 2020). Hence, humanoid robots in frontline service may not be a vantage factor (Hui et al., 2004) with the concurrent presence of human employees as they are in substituting for conventional self-service machines.

Humanoid robots and psychological risk. Contrary to our initial hypothesis, not all aspects of humanoid robots are favorably received by consumers. This is reflective of the paradoxical nature of new technology in that it brings with it both positive and negative implications for consumers (Mick and Fournier, 1998). We found that consumers perceive increased psychological risk when being served by a humanoid robot as opposed to a self-service machine, though performance ambiguity was unaffected. In general, it is not unusual for new technologies to be met with consumer anxiety (Meuter et al., 2005) and interactions with humanoid service robots are certainly not so commonplace that most consumers are completely at ease with them. Interestingly, the performance of the robot did not seem to be a problematic prospect for consumers (cf. Johnson et al., 2008 in relation to self-service technology), and yet the risk or uneasiness of dealing with it was shown to have some negative impact on expected service quality. The underlying psychological reasons may be found in the (now well-explored) depths of the uncanny valley (Kim et al., 2019; Mori, 1970); or perhaps there is some inherent bias in us against non-human entities that appear/attempt to resemble us (known as speciesism; Schmitt, 2020) manifesting in the negativity towards humanoid robots. Such reasons were enough to prompt one prominent expert to declare "*whatever you do, don't humanize [care] robots*" (van Doorn, 2020). Yet, our results in relation to psychological risk do not completely outweigh the positive side of humanoid robots in frontline service, as there remained a positive direct effect on expected service quality while accounting for the corresponding rise in psychological risk. As such, there may be some scope for humanoid robots in frontline service, which can be further understood by closely examining the role of consumer preferences such as the need for human interaction and technology readiness.

Need for human interaction – foe and friend for robotic service. From our results, NISE is found to be a general consumer tendency, which, irrespective of humanoid robot involvement, acts against technology-driven service provision by increasing perceived psychological risk. While the finding supports previous research on service technologies (e.g., Meuter et al., 2005; Oh et al., 2013; Schaarschmidt and Höber, 2017), it also suggests that the potential negative impact of humanoid robots on eventual service outcomes is not different from that of a self-service machine in terms of consumers' need for human interaction. We observe that the indirect negative influence on expected service quality via psychological risk is negated when NISE is controlled for, and the direct effect of a humanoid service robot (vs. self-service machine) is positive under the same condition. This, and findings from similar work on consumer preference for anthropomorphic chatbots (Sheehan et al., 2020), provide positive potential for averting deleterious service outcomes of humanoid robots, even though consumers perceive greater psychological risk when dealing with a humanoid robot as opposed to a self-service machine.

Technology readiness as a key factor in determining robotic service outcomes. Many theorists have predicted that consumer technology readiness would play an important role in determining the acceptance or adoption of robot-delivered services (e.g., Mende and Noble, 2019; Mende et al., 2019; Xiao and Kumar, 2021). However, to our knowledge, no prior empirical work has specifically investigated the role of technology readiness with respect to humanoid service robots and their impact on consumer service perceptions. Adopting the established measurement of the Technology Readiness Index (TRI) (Parasuraman, 2000; Parasuraman and Colby, 2015), we show that a humanoid robot's effect on expected service quality is positive for all but low levels of technology readiness. This is in line with prior investigations on service technologies in general (Meuter et al., 2005; Wang et al., 2017). In addition, while the direct effect on visit intention is negative for low technology readiness, the indirect effect is positive via expected service quality, which can be understood by returning to earlier discussions on vantage and qualifying factors (Hui et al., 2004). This result reiterates that service quality is requisite for humanoid robots to be viewed as a vantage factor for consumers, so that they are tempted to visit the robot service provider.

Managerial Implications

Given the favorable influence on visit intention and willingness to pay, as well as the infusion of comparatively greater warmth and competence than a typical self-service machine, at the outset, it seems advisable for certain forms of services to invest in more humanoid service technology. The current consensus seems to be that humanoid service robots are a preferred option where human frontline employees are too costly to employ or where the robots can supplement the human service delivery through physical strength, computing power etc. (Huang and Rust, 2018; Susskind, 2020; Wirtz et al., 2018). Our studies illustrate that humanoid robots delivering frontline service is in fact advantageous over the use of conventional self-service technology, especially because they can gain more favorable cognitive evaluations from consumers by increasing warmth and competence inferences. Given this, and the potential for humanoid robots to be a differentiating factor, service managers could deploy humanoid robots for fully automated service where warmth, as well as competence, is desired by consumers (e.g., hotel reception).

Moreover, under special circumstances such as where physical distancing is required due to the spread of disease, such ability to bring warmth as well as competence to service delivery can be greatly appreciated by consumers who may be forced to deal with humanoid robots instead of human service staff (due to unavailability of human staff, and not necessarily because of job displacement). For example, at the Third People's Hospital of Shenzhen (China), humanoid robots receive and direct visitors (as well as take their temperature) and help medical staff to speak to patients and each other safely via videoconferencing (Ackerman et al., 2020).

In parallel however, the psychological risk perceptions induced by humanoid robots can be a cause for concern. Thus, service managers should be careful in the implementation of humanoid service robots and not neglect (sub)conscious consumer concerns regarding these technologies. Nevertheless, even at the prospect of raising psychological risk perceptions, humanoid robots' ultimate influence on expected service quality remains positive. Hence, given our results relating to the overall positive effect on central consumer intentions towards the service, as well as warmth and competence perceptions of humanoid robots, ideally, managers should strive to emphasize the positive elements to counterbalance the influence of psychological risk. The key to achieving this depends on knowing the extent to which consumers have an innate tendency to seek human interaction in service scenarios. Service managers may segment consumers based on their underlying tendency for seeking human service staff contact, and thus tailor the service provisions accordingly to mitigate the psychological risk.

Nevertheless, in comparison to humans, our findings show that service robots are not perceived to be more warm or competent. As such, in supplementing human-provided services with robots, service managers could be assigned to achieve specific purposes or tasks that are part of the service provision, but not form the whole service offering. Tasks given to humanoid robots could be more complex or inefficient for human counterparts, and would leave human staff to handle aspects of the service offering that require more of a human touch (e.g., 'feeling' services; Huang and Rust, 2021). Also, having human help at hand to compensate for *potential* performance issues may be necessary, but perhaps the human staff's presence need not be physical (e.g., they could be 'tele-present').

In any event, consumer acceptance of augmented or fully automated robotic services will be influenced by their technology readiness. Based on the technology readiness index, for low technology readiness consumers, deployment of humanoid robots in frontline services seems at best to have no effect on their service expectations and at worst to negatively influence visit intention. Nevertheless, our results support the use of humanoid robots for average and high technology readiness consumers, which would represent the mainstream market in most cases, provided that service providers are able to meet the higher service quality expectations that accompany humanoid robot-delivered service.

A case example that combines many of our managerial observations is KFC's AI-enabled humanoid robot Dumi, which was launched in 2017 in China. Developed by Baidu, Dumi combines many sophisticated machine learning models to bring facial recognition, voice recognition, and online data mining capabilities to frontline service alongside human staff for a specific purpose: to engage with consumers speaking different dialects of the Chinese language and automatically determine customized offerings for them (Chen, 2017). There is an obvious cost advantage compared to employing human staff. Nevertheless, a key reason for its success is attributable to careful targeting of segments that are high in technology readiness motivations, despite some concern for data privacy, and have good reason to avoid human staff – language differences that make them feel embarrassed and often insulted when speaking with human staff (*ibid*).

Limitations and Future Research

Since consumer experience with humanoid robots in frontline service has yet to be broadly established, our studies utilized the scenario-based experimental methodology (as have previous researchers, e.g., Jörling et al., 2019). Experimental studies involving actual robot-human interactions would be more appropriate for measuring specific features (e.g., human-robot eye contact during interaction) and may come with certain limitations of their own (e.g., sample sizes, time, and resource constraints). However, additional insights could be gained from such studies, especially pertaining to real-time and post-consumption experiences. Nonetheless, there are some differences that we may expect when comparing imagined interactions to actual human-robot interactions. For instance, a robot's behavior should match its (humanlike) appearance in order to elicit positive evaluations from users when interacting with humanoid robots (Walters et al., 2008). Users also do not readily understand the behavior of robots (Thellman and Ziemke, 2020), and interpretations of robot behavior can differ between different users at a neuro-physiological level (Bossi et al., 2020; Ziemke, 2020).

In addition, according to other theorists (e.g., Xiao and Kumar, 2021; van Doorn et al., 2017), there are many other factors that need to be considered in determining the degree of robotic automation of the service frontlines, including employee acceptance of robots as well as consumer acceptance. Hence, further research is required to examine these factors and their interplay in more detail. Moreover, considering the degree of robot automation, future research should also examine how varying levels of human social presence could affect consumer responses. In addition, various aspects of the situation (e.g., service failure), as well as characteristics of the individual involved (e.g., introversion-extroversion), will determine the nature and extent of the emotions and responses that service robots induce (de Graaf and Allouch, 2013; Walters et al., 2008).

Despite the evidence from our research that consumers differ in terms of underlying preferences, at present, only technology readiness segments have been identified and described in detail (Parasuraman and Colby, 2015). Hence, developing a deeper understanding of specific segments in the population that differ in terms of their preferences (e.g., type of role or features of robots) and attitudes (e.g., affinity vs. aversion) towards robots would enable better targeting and positioning strategies.

Due to rapid technological development coupled with relatively quick commercial adoption and deployment of robots in retail and service frontlines, consumer attitudes can change faster than anticipated, especially compared to self-service machines. Unforeseen macroenvironmental forces such as the COVID-19 pandemic can also trigger renewed interest in many forms of technologies, including robots (Howard and Borenstein, 2020). For example, university graduation ceremonies during the pandemic have been held using robots for safety reasons (Reuters, 2020). Hence, researchers should investigate how the public's perspective on humanoid robots evolves over time, or changes drastically due to sudden events, and consider the factors that influence such changes.

Nonetheless, changes in consumer attitudes towards humanoid robots can be negative, as well as positive, and will entail myriad ethical implications that urgently need addressing, both practically and theoretically (Belk, 2020). Robots in retail and service may become commonplace due to mainstream commercial adoption, and researchers may have to investigate consumer acquiescence or even potential resistance in this case. Also, researchers have so far focused on the displacement of jobs, but there are many other areas needing more investigation, including data security and privacy violation by embodied artificial intelligence (e.g., Dumi), military and sex robots becoming widely available, robots as managers of human employees, and of course, the 'leftover' roles for humans in their economic lives when robotic automation is ubiquitous (Belk, 2020; Howard and Borenstein, 2020; Robert et al., 2020; Susskind, 2020).

Finally, research should also focus on more positive elements of robotic service automation. For example, in Japan, severely disabled or paralyzed people are given the opportunity to work in service frontlines using a remotely controlled (humanoid) robot (World Economic Forum, 2018). Such empowerment (as opposed to displacement) through robotic automation warrants further attention, so that we may perhaps shape the future of robotic automation to be more beneficial to humankind.

Concluding Notes

Though much conceptual work exists on the influence of humanoid robots in frontline services, empirical work is still at an early stage. The current study is another step towards the understanding of the impact of humanoid robots on service perceptions. Our research examined the comparative influence of humanoid service robots vs. conventional self-service technology on service perceptions and social cognition in the presence/absence of human service employees. Further examination was made based on consumers' need for interaction with human staff and their technology readiness. Subsequently, we discussed benefits and drawbacks of humanoid robots in frontline service and considered relevant managerial implications as well as future research areas.

REFERENCES

Ackerman, E., Guizzo, E., & Shi, F. (2020). Robots Help Keep Medical Staff Safe at COVID-19 Hospital. *IEEE Spectrum*. Retrieved from: https://spectrum.ieee.org/automaton/robotics/robotics-hardware/video-friday-ubtech-robots-covid-19-shenzhen-hospital

Barrutia, J. M., & Gilsanz, A. (2012). Electronic service quality and value: Do consumer knowledge-related resources matter? *Journal of Service Research, 16*(2), 231-246.

Belk, R. (2020). Ethical issues in service robotics and artificial intelligence. *The Service Industries Journal*, 1-17. doi:10.1080/02642069.2020.1727892

Blut, M., & Wang, C. (2020). Technology readiness: A meat-analysis of conceptualizations of the construct and its impact on technology usage," *Journal of the Academy of Marketing Science,* 48, 649-669.

Bossi, F., Cesco, W. Jacopo, C. Marchesi, S., Murino, V., & Wykowska, A. (2020). The human brain reveals resting state activity patterns that are predictive of biases in attitudes toward robots. *Science Robotics, 5*(46), eabb6652.

Chen, C. (2017). KFC Dumi: AI Service Robot. *WARC*. www.warc.com

Choi, Y., Hickerson, B., & Kerstetter, D: (2018). Understanding the Sources of Online Travel Information. *Journal of Travel Research* 57(1), 116–28.

Collier, J. E., & Kimes, S. E. (2012). Only if it is convenient: Understanding how convenience influences self-service technology evaluation. *Journal of Service Research, 16*(1), 39-51.

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: An investigation of alternative models of service quality. *International Journal of Research in Marketing, 13*(1), 29-51.

Davenport, T., Guha, A., Grewal, D:, & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24-42.

de Graaf, M. M. A., & Allouch, S. B. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems, 61*(12), 1476-1486.

de Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy and information sharing into visitors' intentions to use social robots. *Tourism Management, 78*, 104042.

Doornik, J. A., & Hansen, H. (2008). An omnibus test for univariate and multivariate normality. Oxford Bulletin of Economics and Statistics 70: 927–939.

Duffy, B. R. (2003). Anthropomorphism and the social robot. *Robotics and Autonomous Systems, 42*(3-4), 177-190.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864-886.

Ferreira, J. B., da Rocha, A., & Ferreira da Silva, J. (2014). Impacts of technology readiness on emotions and cognition in Brazil. *Journal of Business Research, 67*, 865-873.

Fiske, S. T., Cuddy, A. J. C., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and Competence. *Trends in Cognitive Sciences, 11*(2), 77-83.

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. 2nd Edn. New York: Guilford Press.

Heerink, M., Kroese, B., Evers, V., & Wielinga. B. (2010). Relating Conversational Expressiveness to Social Presence and Acceptance of an Assistive Social Robot. *Virtual Reality, 14*(1), 77-84.

Ho, T. H., Tojib, D., & Tsarenko, Y. (2020). Human staff vs. service robot vs. fellow customer: Does it matter who helps your customer following a service failure incident? *International Journal of Hospitality Management, 87*, 102501.

Horstmann, A. C., Bock, N., Linhuber, E., Szczuka, J. M., Straßmann, C., & Krämer, N. C. (2018). Do a robot's social skills and its objection discourage interactants from switching the robot off? *PLOS ONE, 13*(7), e0201581.

Howard, A., & Borenstein, J. (2020). AI, Robots, and Ethics in the Age of COVID-19. *MIT Sloan Management Review*. Retrieved from https://sloanreview.mit.edu/article/ai-robots-and-ethics-in-the-age-of-covid-19/

Huang, M.-H., & Rust, R. T. (2017). Technology-driven service strategy. *Journal of the Academy of Marketing Science, 45*, 906-924.

Huang, M.-H., & Rust, R. T. (2018). Artificial Intelligence in Service. *Journal of Service Research, 21*(2), 155-172.

Huang, M.-H., & Rust, R. T. (2021). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research, 24*, 30-41.

Huang, M.-H., Rust, R. T., & Maksimovic, V. (2019). The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI). *California Management Review, 61*(4), 43-65.

Hui, M. K., Zhao, X., Fan, X., & Au, K. (2004). When Does the Service Process Matter? A Test of Two Competing Theories. *Journal of Consumer Research, 31*(2), 465-475.

Jacoby, J., & Kaplan, L. B. (1972). The components of perceived risk. SV – Proceedings of the third annual conference of the Association for Consumer Research, 382-393.

Jörling, M., Boehm, R., & Paluch, S. (2019). Service robots: Drivers of perceived responsibility for service outcomes. *Journal of Service Research, 22*, 404-420.

Johnson, D. S., Bardhi, F., & Dunn, D. T. (2008). Understanding how technology paradoxes affect customer satisfaction with self-service technology: The role of performance ambiguity and trust in technology,. *Psychology & Marketing, 25*(5), 416-443.

Kim, S. Y., Schmitt, B. H., & Thalmann, N. M. (2019). Eliza in the uncanny valley: anthropomorphizing consumer robots increases their perceived warmth but decreases liking. *Marketing Letters, 30*(1), 1-12.

Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., Wuenderlich, N. V., & de Keyser, A. (2017). Service Encounter 2.0": An investigation into the roles of technology, employees and customers. *Journal of Business Research, 79*, 238-246.

Lee, S., & Oh, H. (2020). Anthropomorphism and its implications for advertising hotel brands. *Journal of Business Research*, doi: 10.1016/j.jbusres.2019.09.053

Lee, K. M., Peng, W., Jin, S.-A., & Yan, C. (2006). Can Robots Manifest Personality?: An Empirical Test of Personality Recognition, Social Responses, and Social Presence in Human–Robot Interaction. *Journal of Communication, 56*(4), 754-772.

Li, J., Bonn, M. A., & Haobin Ye, B. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management, 73*, 172-181.

McLeay, F., Osburg, V.-S., Yoganathan, V., & Patterson, A. (2021). Replaced by a Robot: Service Implications in the Age of the Machine. *Journal of Service Research, 24*, 104-121.

Mende, M., & Noble, S. M. (2019). Retail Apocalypse or Golden Opportunity for Retail Frontline Management? *Journal of Retailing, 95*(2), 84-89.

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535-556.

Meuter, M. L., Bitner M. J., Ostrom, A. L., & Brown, S. W. (2005). Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. *Journal of Marketing, 69*(2), 61-83.

Mick, D. G., & Fournier, S. (1998). Paradoxes of technology: Consumer cognizance, emotions, and coping strategies. *Journal of Consumer Research, 25*(2), 123-143.

Mori, M. (1970). The uncanny valley. *Energy, 7*(4), 33-35.

Murphy, J., Gretzel, U., & Pesonen, J. (2019). Marketing robot services in hospitality and tourism: The role of anthropomorphism. *Journal of Travel & Tourism Marketing*, doi: 10.1080/10548408.2019.1571983.

Oh, H., Jeong, M., & Baloglu, S. (2013). Tourists' adoption of self-service technologies at resort hotels. *Journal of Business Research, 66*, 692-699.

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307-320.

Parasuraman, A., & Colby, C. L. (2015). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research, 18*(1), 59-74.

Park, S. (2020). Multifaceted trust in tourism service robots. *Annals of Tourism Research, 81*, 102888.

Reimann, M., Luenemann, U. F., & Chase, R. B. (2008). Uncertainty avoidance as a moderator of the relationship between perceived service quality and customer satisfaction,. *Journal of Service Research, 11*(1), 63-73.

Reuters. (2020). COVID-19 robot patrol rolled out in Belgian hospitals. Retrieved from https://www.reuters.com/article/us-health-coronavirus-belgium-robots-idUSKBN2352ES

Robert, L. P., Pierce, C., Marquis, L., Kim, S., & Alahmad, R. (2020). Designing fair AI for managing employees in organizations: a review, critique, and design agenda. *Human–Computer Interaction*, 1-31.

Schaarschmidt, M., & Höber, B. (2017). Digital booking services: Comparing online with phone reservation services. *Journal of Services Marketing, 31*(7), 704-719.

Schmitt, B. (2020). Speciesism: an obstacle to AI and robot adoption,. *Marketing Letters, 31*(1), 3-6.

Scott, M. L., Mende, M., & Bolton, L. E. (2013). Judging the book by its cover? How consumers decode conspicuous consumption cues in buyer-seller relationships. *Journal of Marketing Research, 50*(3), 334-347.

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption,. *Journal of Business Research, 115*, 14-24.

Stone, R. N., & Grønhaug, K. (1993). Perceived risk: Further considerations for the marketing discipline. *European Journal of Marketing, 27*(3), 39-50.

Susskind, D. (2020). *A World Without Work: Technology, Automation and How We Should Respond*. London: Penguin Books.

Thellman, S., & Ziemke, T. (2020). Do You See what I See? Tracking the Perceptual Beliefs of Robots. *iScience, 23*(10), 101625.

Tielman, M., Neerincx, M., Meyer, J.-J., & Looije, R. (2014). Adaptive emotional expression in robot-child interaction. *Proceedings of the 2014 ACM/IEEE International Conference on Human-Robot Interaction, ACM*, New York, NY, 407-414.

Touré-Tillery, M., & McGill, A. L. (2015). Who or what to believe: Trust and the differential persuasiveness of human and anthropomorphized messengers,. *Journal of Marketing, 79*, 94-110.

van Doorn, J. (2020). Whatever you do, don't humanize care robots [Press release]. University of Groningen. Retrieved from: https://www.rug.nl/news/2020/01/maak-van-zorgrobot-vooral-geen-mens?lang=en

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal., D., & Petersen, J. A. (2017). Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences. *Journal of Service Research, 20*(1), 43-58.

Verma, V., Sharma, D., & Sheth, J. (2016). Does relationship marketing matter in online retailing? A meta-analytic approach,. *Journal of the Academy of Marketing Science, 44*, 206-217.

Walters, M. L., Syrdal, D. S., Dautenhahn, K., te Boekhorst, R., & Koay, K. L. (2008). Avoiding the uncanny valley: robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion. *Autonomous Robots, 24*(2), 159-178.

Wang, Y., So, K. K. F., & Sparks, B. A. (2017). Technology readiness and customer satisfaction with travel technologies: A cross-country investigation. *Journal of Travel Research, 56*(5), 563-577.

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management, 29*(5), 907-931.

World Economic Forum (2018). In this Tokyo cafe, the waiters are robots operated remotely by people with disabilities. Retrieved from https://www.weforum.org/agenda/2018/12/tokyo-cafe-waiters-robots-disabilities/

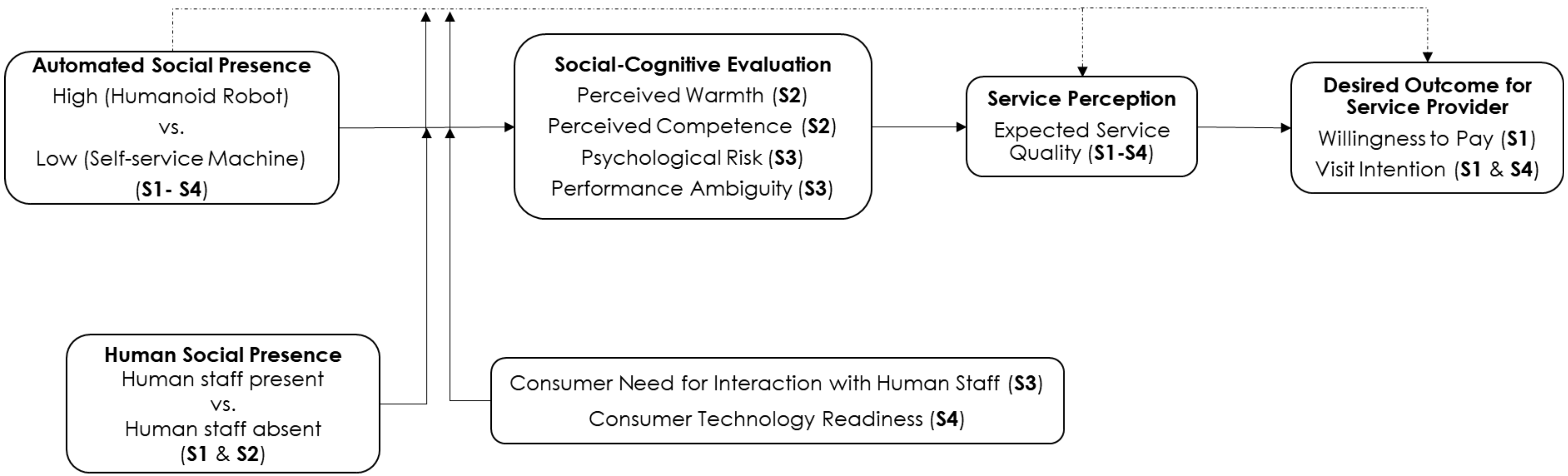
Xiao, L., & Kumar, V. (2021) Robotics for customer service: A useful complement or an ultimate substitute? *Journal of Service Research*, 24, 9-29.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality, *Journal of Marketing, 60*(2), 31-46.

Ziemke, T. (2020). Understanding robots. *Science Robotics, 5*(46), eabe2987.

FIGURES

Figure 1: Conceptual framework



Note: Broken lines indicate an indirect effect.

Figure 2: Mean comparison for Study 1 manipulations

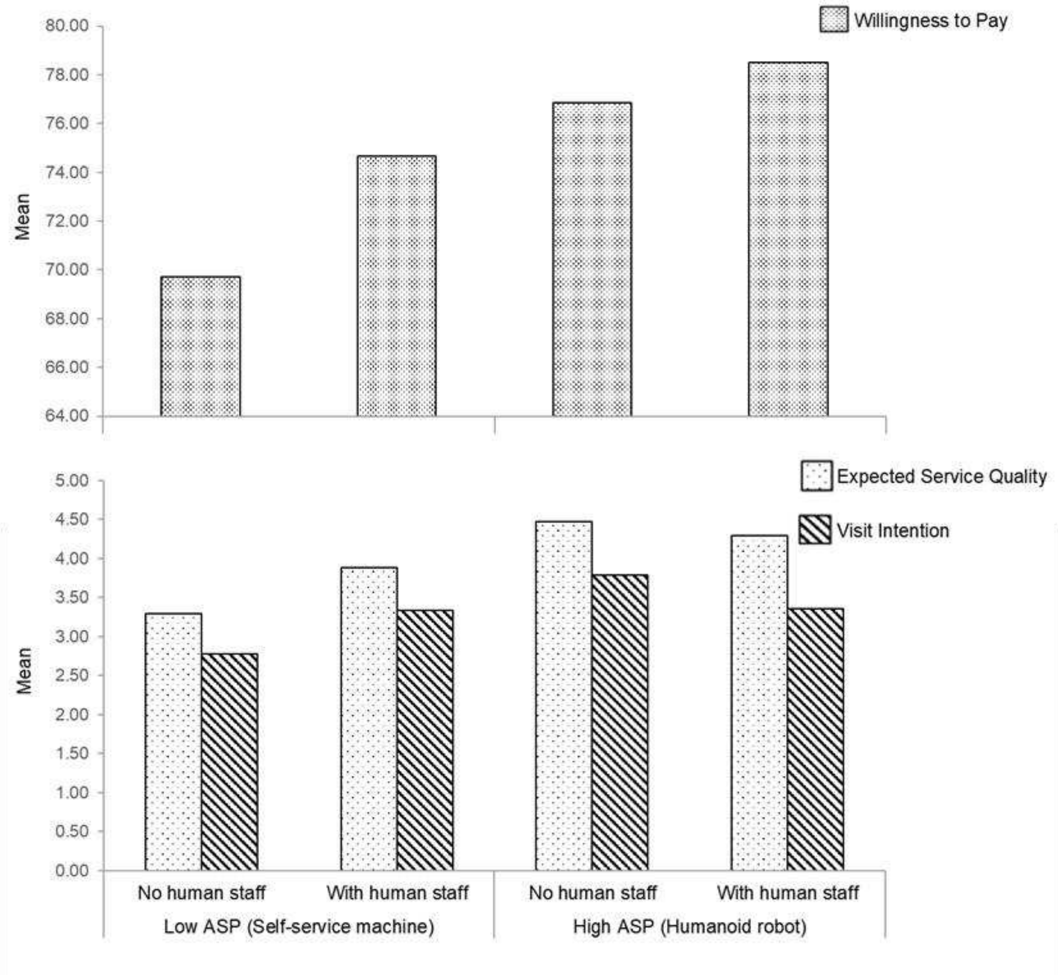


*Figure 3: ASP*HSP interaction effect on expected service quality*

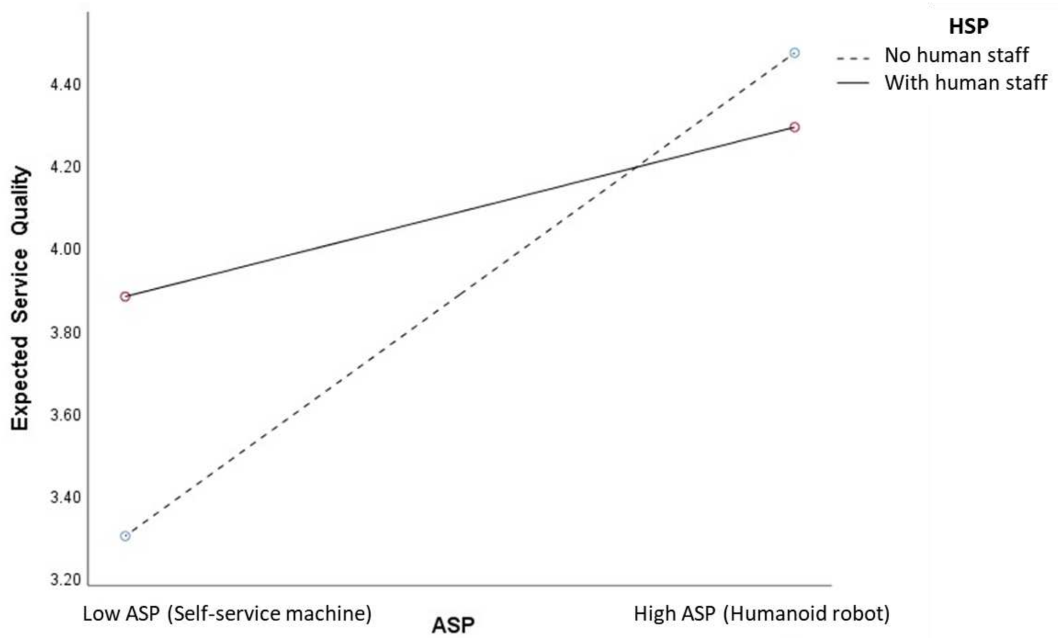


Figure 4: Mean comparison for Study 2

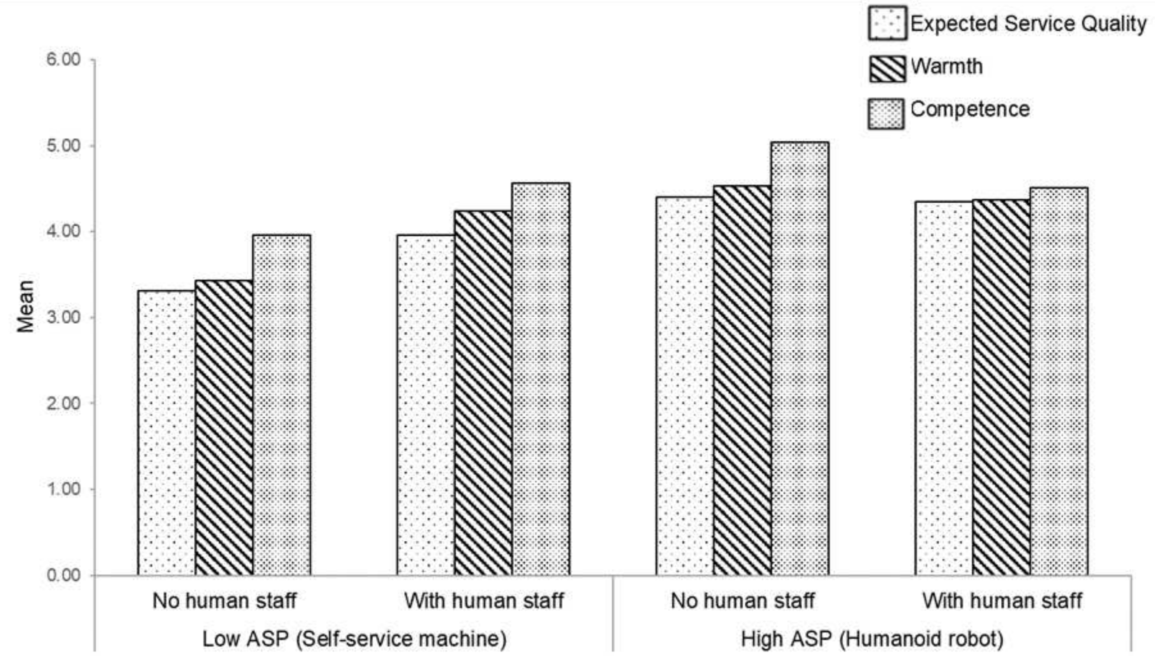


*Figure 5: ASP*HSP interaction effect on warmth*

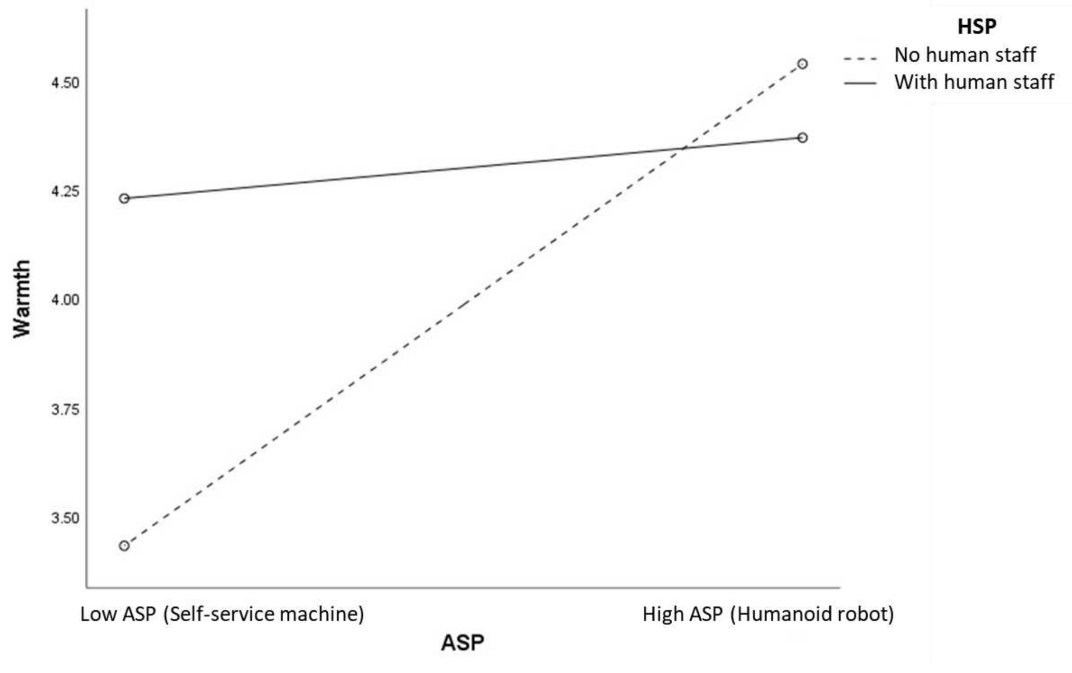


*Figure 6: ASP*HSP interaction effect on competence*

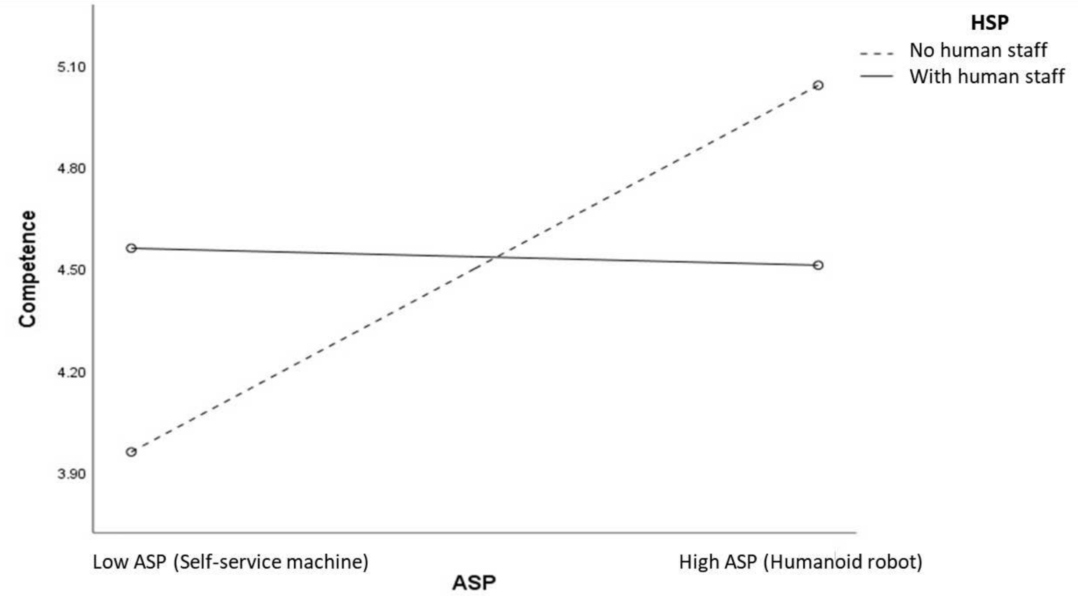


Figure 7: Mean comparison for Study 3

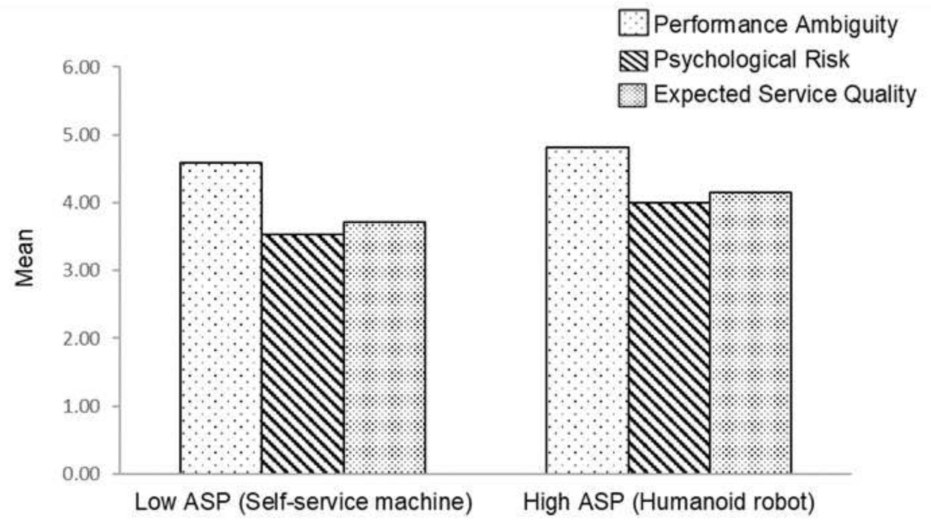


Figure 8: Johnson-Neyman plot for humanoid robot's effect on expected service quality

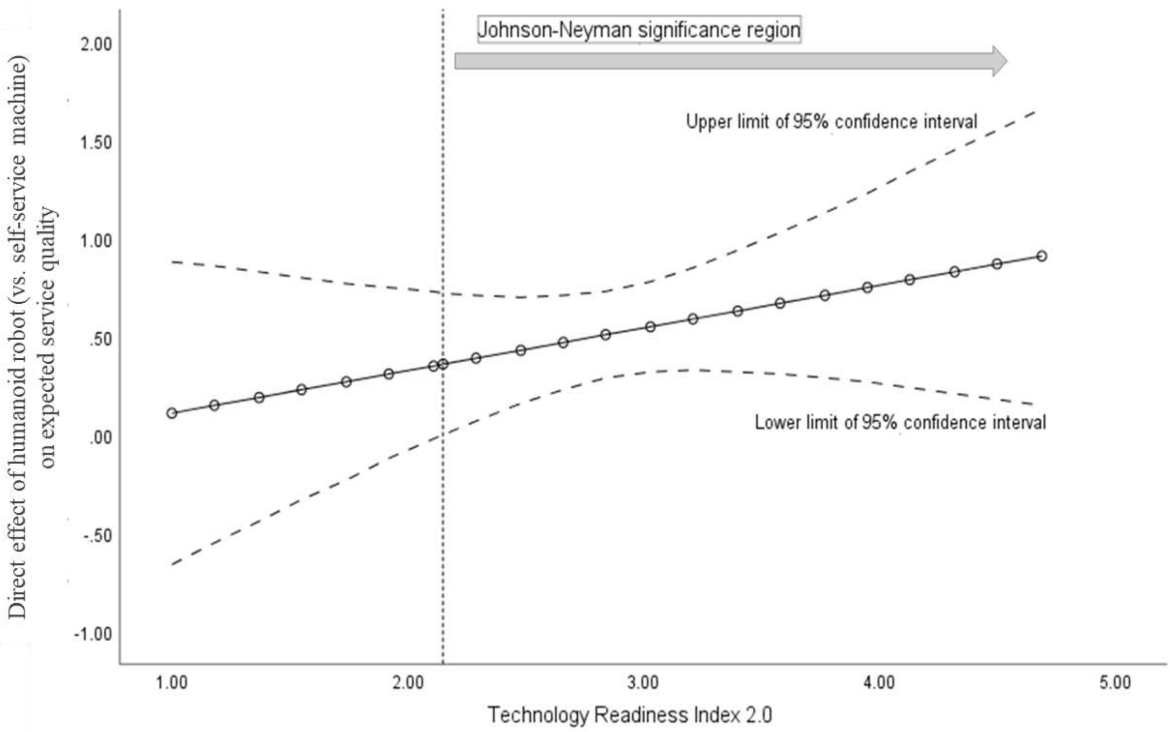
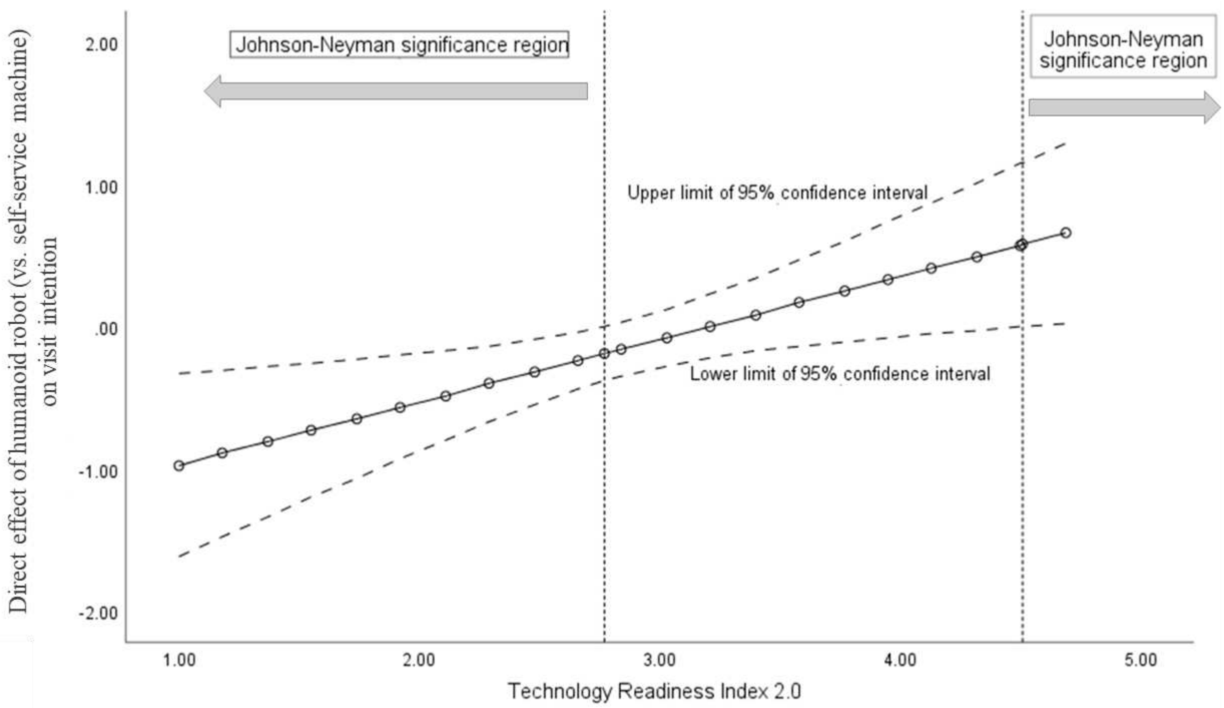


Figure 9: Johnson-Neyman plot for humanoid robot's effect on visit intention



TABLES

Table 1: Overview of PROCESS results for Study 1

Direct effects	*Human Social Presence*	*β*	*SE*	*95% CI*
Humanoid robot (vs. self-service machine) → Expected Service Quality	-	0.39*	0.08	0.23, 0.56
	No human staff	0.59*	0.12	0.35, 0.82
	With human staff	0.20	0.12	-0.03, 0.44
Humanoid robot (vs. self-service machine) → Visit Intention	-	-0.08	0.07	-0.20, 0.05
	No human staff	0.00	0.09	-0.18, 0.19
	With human staff	-0.16	0.09	-0.34, 0.01
Humanoid robot (vs. self-service machine) → Willingness to Pay	-	0.86	1.00	-1.10, 2.83
	No human staff	0.60	1.42	-2.19, 3.38
	With human staff	1.13	1.37	-1.58, 3.83
Expected Service Quality → Visit Intention	-	0.85*	0.04	0.76, 0.94
Expected Service Quality → Willingness to Pay	-	3.87*	1.01	1.88, 5.85
Indirect Effects				
Humanoid robot (vs. self-service machine) → Expected Service Quality → Visit Intention	No human staff	0.48*	0.10	0.30, 0.68
	With human staff	0.17	0.10	-0.04, 0.37
Humanoid robot (vs. self-service machine) → Expected Service Quality → Willingness to Pay	No human staff	2.27*	0.76	0.92, 3.95
	With human staff	0.78	0.54	-0.17, 1.96

Notes: *statistically significant effect; β: unstandardized effect coefficient; SE: bootstrapped standard error; CI: bootstrapped bias-corrected confidence interval.

Table 2: Overview of PROCESS results for Study 2

Direct effects	*Human Social Presence*	*β*	*SE*	*95% CI*
Humanoid robot (vs. self-service machine) → Warmth	-	0.62*	0.15	0.33, 0.91
	No human staff	1.11*	0.20	0.71, 1.50
	With human staff	0.13	0.22	-0.30, 0.57
Humanoid robot (vs. self-service machine) → Competence	-	0.52*	0.16	0.20, 0.83
	No human staff	1.08*	0.22	0.66, 1.51
	With human staff	-0.05	0.24	-0.52, 0.41
Humanoid robot (vs. self-service machine) → Expected Service Quality	-	0.32*	0.11	0.10, 0.55
	No human staff	0.29	0.12	-2.19, 3.38
	With human staff	0.36*	0.17	0.04, 0.69
Warmth → Expected Service Quality	-	0.35*	0.07	0.21, 0.49
Competence → Expected Service Quality	-	0.38*	0.07	0.25, 0.51
Indirect Effects				
Humanoid robot (vs. self-service machine) → Warmth → Expected Service Quality	No human staff	0.39*	0.12	0.18, 0.63
	With human staff	0.05	0.07	-0.09, 0.19
Humanoid robot (vs. self-service machine) → Competence → Expected Service Quality	No human staff	0.41*	0.12	0.20, 0.68
	With human staff	-0.02	0.09	-0.19, 0.17

Notes: *statistically significant effect; β: unstandardized effect coefficient; SE: bootstrapped standard error; CI: bootstrapped bias-corrected confidence interval.

Table 3: Overview of PROCESS results for Study 3

Direct effects	*NISE*	*β*	*SE*	*95% CI*
Humanoid robot (vs. self-service machine) → Psychological Risk	Not in model	0.47*	0.17	0.14, 0.81
	Low (m-1SD)	0.16	0.22	-0.27, 0.60
	High (m+1SD)	0.32*	0.16	0.01, 0.62
Humanoid robot (vs. self-service machine) → Performance Ambiguity	Not in model	0.22	0.14	-0.06, 0.50
	Low	-0.03	0.19	-0.40, 0.34
	High	0.22	0.19	-0.14, 0.59
Humanoid robot (vs. self-service machine) → Expected Service Quality	Not in model	0.57*	0.13	0.31, 0.83
	Low	0.46*	0.19	0.10, 0.83
	High	0.65*	0.19	0.29, 1.02
Psychological Risk → Expected Service Quality	NA (in model)	-0.29*	0.04	-0.38, -0.20
Performance Ambiguity → Expected Service Quality	NA (in model)	-0.04	0.05	-0.14, 0.07
Indirect Effects				
Humanoid robot (vs. self-service machine) → Psychological Risk → Expected Service Quality	Not in model	-0.12*	0.05	-0.22, -0.03
	Low	-0.05	0.06	-0.16, 0.07
	High	-0.14	0.08	-0.30, 0.02
Humanoid robot (vs. self-service machine) → Performance Ambiguity → Expected Service Quality	Not in model	0.00	0.01	-0.04, 0.03
	Low	0.00	0.01	-0.03, 0.03
	High	-0.01	0.02	-0.06, 0.03

Notes: *statistically significant effect; β: unstandardized effect coefficient; SE: standard error; CI: confidence interval; SD: standard deviation; NISE: need for interaction with service employees; NA: not applicable.

Table 4: Overview of PROCESS results for Study 4

Direct effects	*TRI 2.0*	*β*	*SE*	*95% CI*
Humanoid robot (vs. self-service machine) → Expected Service Quality	Low (m-1SD)	0.39*	0.16	0.08, 0.71
	High (m+1SD)	0.64*	0.16	0.32, 0.95
Humanoid robot (vs. self-service machine) → Visit Intention	Low (m-1SD)	-0.40*	0.13	-0.66, -0.13
	High (m+1SD)	0.10	0.14	-0.17, 0.37
Indirect Effects				
High (vs. low) ASP → Expected Service Quality → Visit Intention	Low	0.31*	0.14	0.03, 0.58
	High	0.49*	0.13	0.25, 0.75

Notes: *statistically significant effect; m: mean; β: unstandardized effect coefficient; SE: bootstrapped standard error; CI: bootstrapped bias-corrected confidence interval; TRI: Technology Readiness Index.

APPENDICES

Appendix A: Descriptives for all studies

	Sample Sizes/Frequency			
	(Study 1)	Study2	Study3	Study4
Age	300 (m=48.3, SD=14.3)	334 (m=48.5, SD=14.4)	430 (m=46.6, SD=15.4)	577 (m=47, SD=14.6)
Gender				
Male	142	158	196	279
Female	158	176	234	298
Highest level of education				
School	64	60	22	113
High School	68	84	122	148
College	62	86	108	122
Bachelor's Degree	78	75	134	135
Master's Degree	25	28	40	56
Doctoral Degree	03	01	04	03
Household Income (Categories)				
10,000 or less	59	55	32	111
10,001 to 20,000	54	72	101	103
20,001 to 30,000	54	66	82	109
30,001 to 40,000	48	56	70	95
40,001 to 50,000	29	27	51	52
50,001 to 60,000	39	37	65	73
More than 60,001	17	21	29	34

Appendix B: Check-in scenario descriptions of Study 1 and 2

	Human Social Presence: ***Staff Present***	**Human Social Presence:** ***Staff Absent***
Automated Social Presence: ***High*** *(Humanoid Service Robot)*	Welcome to the reception of your hotel! The check-in is done by the ***robot*** you see in the picture. The robot ***looks like a human***. The hotel is operated by ***robots with the support of human staff***. Therefore, during your stay, you will mainly be interacting with these robots, but human staff may assist you when needed.	Welcome to the reception of your hotel! The check-in is done by the ***robot*** you see in the picture. The robot ***looks like a human***. The hotel is ***fully*** operated by ***robots without the support of human staff***. Therefore, during your stay, you will only be interacting with these robots.
Automated Social Presence: ***Low*** *(SST)*	Welcome to the reception of your hotel! The check-in is done by the self-***service machine*** you see in the picture. The hotel is operated by ***self-service machines with the support of human staff***. Therefore, during your stay, you will mainly be interacting with these machines, but human staff may assist you when needed.	Welcome to the reception of your hotel! The check-in is done by the ***self-service machine*** you see in the picture. The hotel is ***fully*** operated ***by self-service machines without the support of human staff***. Therefore, during your stay, you will only be interacting with these machines.

Note: images for peer review only

Appendix C: Constructs and Items

Constructs and Items	Loadings				Source
	S1	S2	S3	S4	
Expected Service Quality (Cronbach's α > 0.8 for all studies)					Dabholkar (1996)
• What level of service quality would you receive from checking-in with a/b/c? (low – high service quality)	0.94	0.96	0.95	0.94	
• Using a/b/c to check in will provide… (poor – excellent service)	0.95	0.93	0.92	0.95	
• Checking in with a/b/c will provide a high level of service quality. (strongly disagree – strongly agree)	0.92	0.92	0.90	0.91	
Willingness to Pay Imagine that the average rate for a room in a hotel of this category is approx. GBP 95. Based on the information provided in the scenario, how much would you be willing to pay per night for this hotel?					Self-developed
Competence (α=0.94) *I expect the service of this hotel to be:*					Scott et al. (2013)
• Incompetent – competent		0.94			
• Unintelligent – intelligent		0.93			
• Poorly-trained – well-trained		0.95			
Warmth (α=0.83) *I expect the service of this hotel to be:*					Scott et al. (2013)
• Unhelpful – helpful		0.90			
• Unselfish – selfish		0.85			
• Uncaring – caring		0.82			
Performance Ambiguity (α=0.89)					Johnson et al. (2008)
• It is difficult for me to determine whether this technology is executing all of my transactions correctly.			0.90		
• I might never know whether this technology is malfunctioning.			0.92		
• Unless it is brought to my attention, errors in my transactions on this technology could go unnoticed.			0.89		
Psychological Risk (α=0.95)					Stone and Grønhaug (1993)
• The thought of using this technology makes me feel psychologically uncomfortable.			0.94		
• The thought of using this technology gives me a feeling of unwanted anxiety.			0.96		
• The thought of using this technology causes me to experience unnecessary tension.			0.96		
Need for Interaction with Service Employees (α=0.86)					Dabholkar (1996)
• Human contact in providing services makes the process enjoyable for the customer.			0.89		
• I like interacting with the person who provides the service.			0.90		
• Personal attention by the service employee is not very important to me (R). (**item removed due to low loading*)			0.45		

• It bothers me to use a machine when I could talk with a person instead.			0.83		
TRI 2.0© **©These questions comprise the Technology Readiness Index 2.0 which is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. This scale may be duplicated only with written permission from the authors.** *Optimism* (α=0.85) • New technologies contribute to a better quality of life. • Technology gives me more freedom of mobility. • Technology gives people more control over their daily lives. • Technology makes me more productive in my personal life. *Innovativeness* (α=0.84) • Other people come to me for advice on new technologies. • In general, I am among the first in my circle of friends to acquire new technology when it happens. • I can usually figure out new high-tech products and services without help from others. • I keep up with the latest technological developments in my areas of interest. *Discomfort* (α=0.81) • When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do. • Technical support lines are not helpful because they don't explain things in terms I understand. • Sometimes, I think that technology systems are not designed for use by ordinary people. • There is no such thing as a manual for a high-tech product or service that's written in plain language. *Insecurity* (α=0.79) • People are too dependent on technology to do things for them. • Too much technology distracts people to a point that is harmful. • Technology lowers the quality of relationships by reducing personal interaction. • I do not feel confident doing business with a place that can only be reached online.				0.80 0.74 0.82 0.80 0.86 0.78 0.66 0.79 0.69 0.74 0.69 0.63 0.81 0.78 0.77 0.60	Parasuraman and Colby (2015).
Visit Intention I would seek to visit this hotel.					Choi et al. (2018); originally developed by Zeithaml et al. (1996)