The future is now? Consumers' paradoxical expectations of human-like service robots

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Abstract

The increasing adoption of human-like intelligent robots in various services has raised significant social and ethical concerns about their future implications. This study investigates how consumers' perceptions of the future development of anthropomorphic features in service robots influence their expectations and acceptance of this emerging technology. Focusing on human-like appearance and mind, we utilize the expectancy-value theory to propose a conceptual framework that delves into consumers' paradoxical expectations. Through a survey of 486 participants, we examine how these perceptions, combined with levels of technology anxiety, shape psychological expectations and subsequently impact the willingness to adopt service robots. Our findings highlight that consumers' perceptions and anxiety levels predict paradoxical expectations, which in turn influence acceptance. This study contributes by introducing a novel framework, exploring the human-like mind in robot anthropomorphism, and addressing the intricate interplay between consumers' perceptions and service robots.

Keywords: Service robot; Expectancy-value theory; Performance efficacy; Realistic threat; Technology anxiety; Willingness to accept.

1. Introduction

The increasing adoption of service robots in areas such as hotels, restaurants, shopping malls, medical care, and companionship services marks a significant shift driven by technological advances (IFR, 2019; Cuzzolin et al., 2020; Wirtz et al., 2018). These robots, characterized by their autonomy and adaptability, serve as interactive assistants for humans, bridging the gap between technology and everyday life (IFR, 2019; Wirtz et al., 2018). A clear trend in their development is the infusion of anthropomorphic design elements (Pauketat and Anthis, 2022). Equipping service robots with human-like attributes has emerged as a strategic means to enhance the social connection between humans and robots (Mariani et al., 2022; Yogeeswaran et al., 2016). However, overly anthropomorphic design can raise potential pitfalls, including the uncanny valley effect, unsettling perceptions, and ethical concerns (Ostrom et al., 2019; Złotowski et al., 2015). This conflict reflects the paradoxes in service robots - offering numerous potentials for value creation while carrying risks (Du and Xie, 2021). These paradoxes encompass the blend of human-like features in robots, endowing them with human capabilities, and ethical, cybersecurity, and existential issues (Kaplan & Haenlein, 2019). With the increasing popularity of AI applications such as ChatGPT, the anticipation of integrating human-like intelligent robots into everyday life has brought forth significant social and ethical concerns regarding the future development of such robots (Blut et al., 2021; Du and Xie, 2021; Pauketat and Anthis, 2022).

Existing research has shed light on how consumers interact with present-day service robots (de Kervenoael et al., 2020; Mathur and Reichling, 2016; Pelau and Ene, 2018), however, there is a noticeable gap in understanding how consumers perceive and respond to anticipated future trends in service robots. Particularly, the existing literature has primarily concentrated on the physical attributes and appearances of service robots (Du and Xie, 2021; Huang and Rust, 2021; Pauketat and Anthis, 2022). While research on attributing minds to robots exists (e.g., Gray et al., 2007), few studies explore the theory of mind in robots, focusing on their perspective-taking ability (Söderlund, 2022).

The term "mind" does not imply that robots have real human hearts or brains, but rather refers to consumers' perceived capability of robots to imitate some of the cognitive and emotional responses of real humans, akin to how infants imitate adults and exhibit aspects of "theory of mind" (Premack and Woodruff, 1978). Furthermore, the mixed reactions of consumers to the anthropomorphic design of service robots could arise from differences in individual technology-related personalities (Parasuraman, 2000; Parasuraman and Colby, 2015), particularly in terms of varying levels of technology anxiety (Meuter et al., 2003).

The research gap is bridged through this study, which aims to examine how consumers' perceptions of future appearance-related and mind-related anthropomorphism in service robots affect their expectations and acceptance of such robots. Drawing upon the expectancy-value theory (Vroom, 1964; Wigfield and Eccles, 2000; Pekrun, 1992; Scheier and Carver, 2007), we propose a conceptual framework suggesting that consumers may harbor paradoxical expectations driven by their beliefs about the future development of human-like service robots. These expectations, in turn, influence their willingness to accept robots for service delivery. More specifically, while some individuals remain optimistic about enhanced service performance, others express pessimism due to concerns about robots displacing human workers (Złotowski et al., 2017; Du and Xie, 2021). Moreover, these expectations can vary based on individual traits, particularly levels of technology anxiety (Pekrun, 1992), ultimately shaping the inclination to adopt service robots.

We conducted a questionnaire survey with a sample of 486 consumers to test our theoretical framework. The results indicate that consumers' perceptions of future anthropomorphic features of service robots, including human-like appearance and mind, along with their levels of technological anxiety, predict their paradoxical psychological expectations, which in turn, influence their willingness to accept service robots.

The study offers several contributions. First, it develops and tests a new conceptual framework based on the expectancy-value theory to explain how users perceive the future anthropomorphic design of robots and its impact on their acceptance of such technology. Second, it introduces a new dimension, the human-like mind of robot anthropomorphism, to examine the influence of human-like appearance and mind on consumer perception and service performance expectations. Third, it systematically explores the paradoxical beliefs of consumers towards the technological progress of service robots, which determine their acceptance of the technology. Finally, the study uses technology anxiety to explain users' expectations about the future development of service robots. The findings have practical implications for robotic strategies and adoption.

2. Theoretical background and hypotheses

2.1. Expectancy-value theory

Expectancy-value theory suggests that human behavior is influenced by a combination of goals, values, and expectancies (Vroom, 1964; Wigfield and Eccles, 2000). The theory has found extensive application in explaining motivation and success, including in the context of technology use (Ranellucci et al., 2020). It posits that goals provide people with structure and meaning in their lives, while expectancies and values shape their involvement and commitment toward achieving those goals. Therefore, expectations of achieving goals and personal values are important predictors of variables such as willingness to take actions, actual actions taken, and persistence in pursuing goals (Ranellucci et al., 2020).

The value of performing a task consists of four components: three positive values and a cost that is negative (Wigfield and Eccles, 2000). The positive ones are the attainment, intrinsic, and utility values. Attainment value refers to the value attributed to succeeding, intrinsic value refers to the joy and satisfaction gained from taking the action, and utility value is how useful the task is for future plans. Cost refers to what an individual must give up to succeed, such as effort, time, loss of important options, or negative emotions (Ranellucci et al., 2020). In the context of service robots resembling humans in both appearance and mind, typical goals are associated with the anticipated positive values of using such robots, including convenience, consistency, and efficiency. The convenience of having tasks automated, the assurance of consistent service quality, and the potential for enhanced efficiency are factors that contribute to the positive perception of service robots. However, this progress may also bring about negative cost values, including the threat to human identity and employment, and give rise to social and economic challenges.

Expectancy is defined as an individual's belief or confidence in the achievability of the goal. Individuals with high levels of confidence hold an optimistic view and are more likely to take action and remain committed (Scheier and Carver, 2007). Conversely, those who lack confidence may hold a pessimistic view of the outcome and are less likely to take action. For example, consumers with a high expectancy about using service robots may anticipate the efficacy of the robots and the enjoyment of the services provided by the robots (Filieri et al., 2022), and they are more likely to accept service robots in service delivery. In contrast, those who consider service robots as a realistic threat to society may resist using service robots to deliver the services they require.

The expectancy-value theory has also contributed to the understanding of anxiety (Pekrun, 1992). Anticipation of a threat or failing to achieve something important may cause anxiety, which can be a momentary state. However, enduring negative expectancy and value beliefs may lead to habitual anxiety, forming a personality trait of anxiety (Pekrun, 1992). While environmental factors can contribute to the development of anxiety, some individuals may have a genetic predisposition towards anxiety, the so-called genetically based anxiety (Pekrun, 1992). Individuals with high levels of anxiety as a personality trait may experience anxiety in various situations and perceive situations as less favorable and more threatening. For instance, people with high levels of technology anxiety may exhibit a less optimistic perspective regarding the efficacy of service robots in delivering services, while simultaneously fearing that their adoption could lead to unemployment (Scheier and Carver, 2007).

2.2. Paradoxes of service robot anthropomorphism

The evolution of robots has been remarkable. Beginning in manufacturing, they mimicked human muscles and bones for repetitive tasks (Nisson, 2011). Advances in AI provided autonomy and adaptability, driving robots into the service industry (Marinova et al., 2017; Wirtz et al., 2018; Jörling et al., 2019). These service robots include physical embodiments and virtual entities (Wirtz et al., 2018; Jörling et al., 2019). Recent advances include autonomous learning, emotional intelligence, and augmented reality. Service robots can take on perspectives that evoke a "mind." The scope now extends to virtual domains, including AI-driven conversational agents and metaverse virtual robots (Dwivedi et al., 2023; Mariani et al., 2023; Moriuchi, 2021; Zehnder et al., 2021). As technology evolves, service robots continue their transformative journey.

Anthropomorphic design refers to the imitation of human external characteristics, such as physical shape and forms, or capabilities, such as human-like interaction and communication (Fink, 2012). The anthropomorphism of service robots is a vital research topic in the field of human-robot interaction (Choi et al., 2019; Lu et al., 2021; Mariani et al., 2022; Roesler et al., 2021). People not only attribute human-like physical features but also attribute human-like minds to artificial objects (Waytz et al., 2010). The design of a human-like mind in service robots based on the theory of mind capacity pertains to their ability to attribute mental states, such as beliefs, perceptions, thoughts, emotions, desires, goals, and intentions, to their users (Söderlund, 2022; Cuzzolin et al., 2020; Mou et al., 2020).

The anthropomorphic design can evoke paradoxical responses from consumers. On one hand, it can elicit positive social responses from consumers (Eyssel and Kuchenbrandt, 2012). Consumers may unconsciously use stereotypes and heuristics to enhance cognitive efficiency and reduce uncertainty (Fink, 2012), and the human-like features satisfy consumers' social needs (Epley et al., 2007). On the other hand, anthropomorphic design can have certain negative impacts, such as the uncanny valley effects of discomfort or unease (Mori, 1970) and the reduction of users' perceived autonomy and control (e.g., Kim et al., 2016; Jörling et al., 2019). These impacts can negatively affect the user experience, especially in contexts where autonomy holds significance (Kim et al., 2016). Consequently, while some people commend the remarkable capabilities of robots, some others express concerns that these robots might replace or harm humans (Du and Xie, 2021). This inconsistency illustrates the inherent paradoxes in service robots. While they offer impressive possibilities, they also carry potential risks. These paradoxes pertain to the dilemma between robots with human-like features, equipping human task-executing capabilities and a host of issues of ethical decision-making, cybersecurity, job loss, and robot-human objective alignment. The continuous advance in service robots makes these issues even more critical (Kaplan & Haenlein, 2019). However, the existing literature on service robots has not adequately examined consumers' these paradoxical expectations.

To foster a fuller understanding of consumer attitudes and responses to service robots, a salient area worthy of scholarly exploration concerns the influence of individual characteristics, particularly technology anxiety levels, in shaping consumers' perceptions and expectations of the evolving service robot landscape. This dimension, though understudied in the existing literature, holds a promising potential to illuminate the intricate cognitive dynamics at play. Furthermore, a discernible gap in the current academic discourse lies in the limited application of expectancy-value theory to elucidate the paradoxical expectancy constructs that underlie consumers' perspectives on future service robot development. Such a theoretical infusion, rooted in the field of motivational psychology, offers a novel vantage point from which to unravel the intricate fabric of consumer expectations.

2.3. Hypothesis development

2.3.1. Paradoxical expecations

Consumer perceptions of progress in anthropomorphic design for service robots are likely to increase expectations for the performance efficacy of service robots (Mou et al., 2020). Expected performance efficacy refers to a user's belief in the ability of future service robots to provide consistent and efficient service in human-robot interaction (Venkatesh et al., 2003). Performance efficacy can be considered a utility value in the expectance-value model (Wigfield and Eccles, 2000). Utility value to the usefulness individuals perceive in completing a task to achieve their short- or long-term goals (Eccles and Wigfield, 2020). In other words, utility value relates to individuals' perceptions of a task's relevance or usefulness for their future objectives. Individuals who place a high utility value on service robots consider them essential because they help them obtain the services they require. Performance efficacy is also closely related to perceived usefulness in the model of technology acceptance (Davis et al., 1989). Prior studies have shown that anthropomorphism and autonomy can increase consumer perceptions of social presence, cooperation, and perceived performance efficacy (Laban and Araujo, 2019; Li and Wang, 2022).

Consumers anticipate that future robots with human-like appearances and cognitive abilities will provide better service performance by virtue of their increased social intelligence and analytical and computing capabilities. The anthropomorphic appearance and mind of future robots are likely to make interactions more habitual, flexible, and interpersonal, which potentially raises consumers' expectations of their performance efficacy (Epley et al., 2007). Thus,

H1: Perception of the future robotic human-like appearance is positively related to expected performance efficacy.

H2: Perception of the future robotic human-like mind is positively related to expected performance efficacy.

While the service efficacy of human-like AI-enabled products is desirable, there will be also concerns about the darker side of the robotic evolution (Du and Xie, 2021). In general, people tend to react positively to ingroups but see outgroups as threats (Yogeeswaran et al., 2016). As robotic anthropomorphism continues to evolve, it may blur the boundaries between human and robot identities. When robots are sufficiently human-like, consumers may perceive them as outgroups that pose a realistic threat to society (Yogeeswaran et al., 2016; Złotowski et al., 2017). A realist threat refers to the perception of actual or tangible risks posed by a particular source or entity, such as service robots, to the safety, well-being, and material resources of a particular group or individuals (Złotowski et al., 2017). The realistic threat is cost value in the expectancy-value framework.

Based on the expectancy-value theory, the cost value could arise from what an individual has to sacrifice or give up, how much effort they need to exert, or how it emotionally affects them to complete a task (Ranellucci et al., 2020). These factors can lower a person's motivation to engage in the task. Cost value has four components: task effort, outside effort, loss of important options, and negative emotion. For instance, a consumer might perceive using a robot as requiring excessive time and effort, resulting in high task effort costs. Alternatively, the consumer might believe that they have too many other responsibilities, such as learning to interact with robots, leading to high outside effort costs. They may also perceive the interaction with robots as replacing valued alternatives such as human interaction, signifying a loss of valued alternatives. Lastly, the negative effect on their emotional well-being of engaging with robots could be considered an emotional cost.

The realistic threats posed by human-like robots is gradually emerging, such as the uncanny valley effect (Mende et al., 2019; Murphy et al., 2019), i.e., when the degree of anthropomorphism in appearance exceeds a certain level, it triggers feelings of discomfort and creepiness (Mori, 1970). Ferrari et al. (2016) found that when a robot is designed to have a real human-like appearance, it raises the highest threat concern. In addition, human-like service robots may threaten non-standardized job positions, especially as they become increasingly indistinguishable from humans in appearance and behavior. This could lead to large-scale human unemployment and challenge societal values (Yogeeswaran et al., 2016; Filieri et al., 2022), threatening human identity, uniqueness, safety, and resources (Złotowski et al., 2017). Thus,

H3: Perception of the future robotic human-like appearance is positively related to expected realistic threats.

H4: Perception of the future robotic human-like mind is positively related to expected realistic threats.

2.3.2. Technology anxiety

Technology anxiety refers to a complex set of emotions that people experience when interacting with technology, such as nervousness, fear, and apprehension (Meuter et al., 2003). It can be considered as a relatively stable personality trait (Pillai and Sivathanu, 2020; Sharma et al., 1981). Generally, individuals with high technological anxiety tend to display timidity, negative tendencies, and avoidance of the use of new technological applications such as service robots (Nomura et al., 2006).

According to the expectancy-value theory (Pekrun, 1992), anxiety can be classified into three types: genetically based anxiety, cognitively mediated anxiety, and habitualized anxiety. Genetic anxiety can occur in early life due to perceived physical danger or deprivation of basic needs. In recurring situations, anxiety mediated by cognitive appraisals can become habitualized, where appraisals are no longer necessary, and anxiety is triggered directly by perceptions of the situation (Pekrun, 1992). Habitualized anxiety may lead to a personality trait of anxiety, resulting from enduring negative expectancy and value beliefs. Individuals with high levels of anxiety as a personality trait may experience anxiety in various situations and perceive situations as less favorable and more threatening. Therefore, we posit that individuals with high levels of technological anxiety are more likely to be pessimistic and perceive negative realistic threats from the service robots, whereas those with low levels of technology anxiety are more likely to be optimistic about the potential positive improvements in service efficacy. Thus,

H5: Technology anxiety is negatively related to expected performance efficacy of service robots.

H6: Technology anxiety is positively related to expected realistic threats of service robots.

2.3.3. Acceptance of service robot

The expectancy-value theory holds that an individual's motivation to conduct or avoid an action is related to their positive or negative valent expectation about the potential outcome of that action (Vroom et al., 2005). Individuals who hold an optimistic view are more likely to take action toward achieving their goals, while those who hold a pessimistic view are less likely to do so (Scheier and Carver, 2007). Based on this, it can be inferred that high expectations for the performance efficacy of service robots may lead to the acceptance of their use in service delivery while seeing service robots as a realistic threat to society may lead to the resistance of their application.

The willingness of users to accept service robots includes their overall psychological acceptance of robots in terms of approval, usage, and adoption intention (de Kervenoael et al., 2020; Gursoy et al., 2019; Ostrom et al., 2019). Acceptance of robots in this context is a multifaceted construct that reflects consumers' opinions about robots in society as a whole, beyond just their use in specific service contexts. Previous empirical studies have suggested a positive link between perceived performance efficacy (usefulness) and positive attitude, trust, adoption, and acceptance of service robots (e.g., Chatterjee et al., 2021; Choung et al., 2022; Go et al., 2020; Park et al., 2021). In contrast, other studies have found that a perceived realistic threat can lead to prejudice, discrimination, and conflict between groups (Yogeeswaran and Dasgupta, 2014). Negative expectations of realistic threats can lead to avoidance of service robots, reducing their willingness to accept them (Ostrom et al., 2019; Lu et al., 2021; Khaliq et al., 2022; Huang et al., 2021). Thus,

H7: Expected performance efficacy of service robots is positively related to willingness to accept service robots.

H8: Expected realistic threats of service robots is negatively related to willingness to accept service robots.

<Insert Figure 1 about here>

3. Methods

3.1. Data collection and participants

The study targeted general consumers as participants through the Credamo platform, which has a good reputation and is frequently used in research studies across diverse areas, similar to Amazon Mechanical Turk (e.g., Li et al., 2022; Su et al., 2021). The Credamo platform has 2.8 million active users and strict selection criteria in terms of participant characteristics (www.credamo.com). The study was conducted between August and September 2022. Participants were offered an incentive of CNY5.00 (equivalent to USD 0.7) once they have submitted the questionnaire. Attention check items and minimum duration were set. In order to ensure that participants could accurately understand the service robot context in this study, we provided an introduction at the beginning of the questionnaire. We defined the scope of service robots, provided examples of physical robots (e.g., Pepper) and virtual robots (e.g., Replika) that are already widely used, and introduced some conceptual robots that we believe will emerge in the future (see the appendix).

Out of the 589 participants who took part in the survey, we excluded 89 responses that failed the attention test and 14 responses that responded exactly the same to all research variable items. This left us with 486 usable responses, which corresponds to an effective rate of 82.51%. To further ensure the validity of the results, we employed conservative statistical methods to detect any potential non-response bias. To do this, we followed the approach recommended by Armstrong and Overton (1977) and divided the sample into two groups based on the time sequence of questionnaire submission. We then conducted a t-test analysis to compare the early and late respondents. The findings of the difference analysis demonstrated that demographic characteristics, such as age (t= 0.01, p> 0.10), education (t= 0.35, p> 0.10), employment status (t= 0.13, p> 0.10), monthly income (t= 0.41, p> 0.10) did not differ significantly between the two samples, neither did willingness to accept service robots (t= 0.23, p> 0.10). Thus, the non-response bias is an issue of concern.

Out of the 486 respondents, 41.56% identified as male and the mean age was 31.17 years. Of those surveyed, 69.55% held a bachelor's degree, while 18.72% had a master's degree or higher. When it comes to income, 39.27% reported earning between CNY 8,001 and 15,000 per month, and 25.31% reported earning between CNY 5,000 and 8,000 per month. The vast majority, or 86.63%, were employed, while the remaining 13.37% included students, unemployed individuals, and retirees.

3.2. Construct measures

The self-reported questionnaire included the following variables: perception of current and future robotic human-like appearance, perception of current and future robotic human-like mind, technology anxiety, expected performance efficacy, expected realistic threat, and willingness to accept service robots, as detailed in Table 1. We used established measurement scales from previous studies in the field of service robots (e.g., Gursoy et al., 2019; Huang et al., 2021; Mani and Chouk, 2018). All the measurements used 5-point Likert scales from “strongly disagree” (1) to “strongly agree” (5). In addition, we ran a pilot study with the participation of two researchers and several consumers to evaluate the survey questions and identify any potential issues.

The measurement for perception of future robotic human-like appearance was based on a four-item scale proposed by Ferrari et al. (2016). Perception of future robotic human-like mind was measured with a three-item scale from Söderlund (2022). We also measured perceptions of current service robots and treated them as control variables (Lu et al., 2019; Zhu et al., 2020). To operationalize both perceptions of current and future service robots, we followed the approach of Pauketat and Anthis (2022) by asking participants to rate their perceptions of existing service robots in 2022 and separately for anticipated future robots.

To measure technology anxiety, we utilized a four-item scale suggested by Henkens et al. (2021). For expected performance efficacy, we adapted a five-item scale originally developed by Lu et al. (2019). We also employed a four-item scale proposed by Złotowski et al. (2017) to measure expected realistic threats. The measurement of willingness to accept service robots was based on three reverse items adapted from de Kervenoael's (2020) scale, with answer scores reversed during analysis. Previous studies have suggested using reverse questioning to improve data collection quality and avoid false correlations caused by acquiescence responses (Schriesheim and Hill, 1981). However, using reverse questioning for a specific measurement item within a construct can confuse respondents, leading to poor measurement reliability and validity (Stewart et al., 2004). To ensure the overall reliability and validity of all items and to avoid excessive consistency, we utilized reverse measurement in all items of the dependent variable.

3.3. Measurement model

The Smart PLS 3.0 statistical package was used to run the evaluation index of the measurement model. Table 2 presents the loadings of all items which were above 0.70. The values of average variance extracted (AVE) were all greater than 0.50. This suggests that the measurement model has good convergent validity (Hair et al., 2020). The model's internal consistency reliability was assessed using Cronbach's α and composite reliability (CR) values, which were all found to be within the acceptable range of 0.70 to 0.90 for each construct, indicating satisfactory reliability (Hair et al., 2020). As shown in Table 2, the square root values of the AVEs were higher than the correlation coefficient between the variables, indicating that the discriminant validity between variables was good (Hair et al., 2020).

Before testing hypotheses, we first compared individuals' perceptions of current and future anthropomorphic design. As evidenced by the results of the t-test, significant differences were observed between the perceptions of future and current of service robot anthropomorphism. The perceptions of the future state were significantly higher than perceptions of the current state (human-like appearance, $t = 24.14, p < 0.001$; human-like mind, $t = 22.52, p < 0.001$). The results indicate that current and future anthropomorphic perceptions were two distinct constructs.

3.4. Common method bias

To mitigate common method bias (CMB), we implemented strategies such as ensuring respondent anonymity and confidentiality, using attention trap items, and reverse measures (Chatterjee et al., 2021). We also conducted a single-factor Harman's test following Podsakoff et al. (2012) and found that the principal factor explained only 22.9% of the variance, which met the standard requirement of being lower than half of the cumulative explanation rate (64.70%) established by Podsakoff and Organ (1986). Additionally, we included a reflective common method latent, following Liang et al. (2007), composed of all the main constructs' indicators, and found that the majority of the loadings of the method factor were not significant. The average method variance explained (0.0035) was considerably smaller than the average substantive variance explained (0.69), with a ratio of approximately 1:200. These results indicate that CMB was unlikely to be an issue in our study.

4. Results

4.1. Structural model

We applied a partial least square structural equation (PLS-SEM) path modeling approach using Smart PLS 3.0 software (Ringle et al., 2015) to test the hypotheses (H1~H8). The specific proposed model and estimators were shown in Figure 2. After testing the effects, the explanatory and predictive power of the model were further evaluated.

<Insert Table 3 about here>

Table 3 displays the significant path coefficients of the structural model, which were determined by using the bootstrap technique with 5000 bootstrapping subsamples to assess their significance. The results indicated that the perception of future human-like appearance had a significantly positive effect on expected performance efficacy ($\beta = 0.605, t = 10.129, p < 0.001$) after controlling for the impacts of perceptions of current service robot anthropomorphism and demographic variables. Perception of future robotic human-like mind significantly and positively affected expected performance efficacy ($\beta = 0.141, t = 2.634, p < 0.01$), supporting H1 and H2. However, neither perception of future human-like appearance ($\beta = 0.030, t = 0.541, p > 0.05$) nor perception of future robotic human-like mind ($\beta = 0.032, t = 0.584, p > 0.05$) significantly affected expected realistic threat, indicating that H3 and H4 were not supported.

Regarding the role of technology anxiety, the results show significant relationships between technology anxiety and expected performance efficacy ($\beta = -0.108, t = 0.050, p < 0.05$), as well as between technology anxiety and expected realistic threat ($\beta = 0.451, t = 9.415, p < 0.001$) and expected realistic threat, supporting H5 and H6. Finally, both expected performance efficacy ($\beta = 0.146, t = 4.097, p < 0.001$) and expected realistic threat ($\beta = -0.550, t = 13.415, p < 0.001$) significantly impacted willingness to accept service robots, indicating support for H7 and H8. Figure 2 displays the path coefficients and the significance of the research model.

<Insert Figure 2 about here>

4.2. Structural model's predictive power

To determine the model's predictive ability of endogenous constructs, we computed the coefficient of determination (R^2), the effect size (f^2), and construct cross-validated redundancy (Q^2), following guidelines by Hair et al. (2016).

The R^2 values were 0.521 for expected performance efficacy, 0.309 for expected realistic threat, and 0.346 for willingness to accept service robots. According to Cohen's guidelines (1988), the effect sizes of exogenous variables can be classified as small, medium, and large, based on their corresponding f^2 values. Specifically, f^2 values of 0.02, 0.15, and 0.35 are considered to represent small, medium, and large effects, respectively. Thus, the model showed that perception of future human-like appearance had a large effect on expected performance efficacy ($f^2 = 0.418$) and perception of the future robotic human-like mind had a small impact on expected performance efficacy ($f^2 = 0.020$). Both perception of future human-like appearance ($f^2 = 0.001$) and perception of future robotic human-like mind ($f^2 = 0.001$) had a small effect on expected realistic threat.

Technology anxiety had a small effect on expected realistic threat ($f^2 = 0.019$) and a medium effect on expected realistic threat ($f^2 = 0.233$). For willingness to accept service robots, expected performance efficacy showed a small effect ($f^2 = 0.034$) and expected realistic threat showed a large effect ($f^2 = 0.400$). The other paths showed relatively smaller effect sizes ($f^2 < 0.02$). Although most of the effect sizes were smaller than a considerable level, the estimated coefficient β (absolute value) of all significant paths was larger than 0.1 (Cohen, 1988). Additionally, the values of Stone-Geisser's Q^2 were obtained, 0.244 for willingness to accept service robots, 0.275 for expected performance efficacy, and 0.214 for expected realistic threat, indicating a good predictive capability for the corresponding endogenous construct (Geisser, 1974). Hence, the proposed research model was further supported by the satisfactory predictive ability demonstrated at the level of endogenous constructs and their indicators.

4.3. Further analysis

The empirical results largely supported our hypotheses, but the lack of support for H3 and H4 requires further post-analysis. First, the non-significant effect of perception of future human-like appearance on expected realistic threat may be due to the fact that human-likeness in appearance does not necessarily indicate a robot's capacity to replace humans. While most people believe that future robots can have realistic human faces (the mean perception of future human-like appearance is 4.224), they do not perceive this appearance as enough to pose a realistic threat (the mean expected realistic threat is 2.438).

Second, expected realistic threat was not significantly explained by perception of future robotic human-like mind either. We speculate that this may be due to the potential boundary of technology anxiety, which may have masked the main effect in our research model. While technology anxiety is hypothesized as a direct antecedent in our model, it may also affect consumers' sensitivity to technology features as a quasi-moderator in specific contexts (Yang and Forney, 2013; Kang and Namkung, 2019). It is possible that only technologically anxious consumers process the perception of the future robotic human-like mind more pessimistically, strengthening their threat expectations. To test this hypothesis, we constructed the interaction item of technology anxiety x perception of future robotic human-like mind and examined this moderating effect. The results showed a positive and significant effect of this interaction on expected realistic threat $(\beta = 0.110, t = 3.504, p < 0.001)$. We also conducted a simple slope analysis on the moderating path. As shown in Figure 3, the positive effect of perception of future robotic human-like mind on expected realistic threat gradually increased with an increase in technology anxiety levels. This indicates that anxious individuals are more likely to feel realistic threat when they predict that future robots would have a human-like mind, while less anxious individuals would have lower threat expectations.

<Insert Figure 3 about here>

5. Discussion and conclusions

This study aims to offer fresh insights into the future trends of service robots by examining consumers' beliefs and expectations regarding the human-like characteristics of these robots, while also taking into account the consumers' level of technology anxiety. The findings show that consumers' perceptions of future human-like appearance and mind in service robots have a significant impact on their responses.

First, our study reveals that perceptions of future human-like appearance and mind in service robots play a significant role in shaping users' psychological responses, even after controlling for current service robot anthropomorphism perceptions. These perceptions had a direct positive impact on users' expected performance efficacy but not on their expected realistic threats. Further analysis suggests that consumers generally do not consider the human-like appearance of a future robot to be a realistic threat, and only those with high levels of technology anxiety perceive the human-like mind as a potential threat.

Second, our study further revealed that individuals' responses to service robot anthropomorphism vary by their level of technology anxiety. Individuals who exhibit high levels of technology anxiety tend to have a pessimistic view that the realistic threats posed by service robots, while those with low anxiety levels hold optimistic expectations of improved service efficacy. While prior literature on technology anxiety highlights it as a stable personality trait that affects technology acceptance (Parasuraman and Colby, 2015; Pillai & Sivathanu, 2020), this finding of our study shows that technology anxiety also influences expectations of the values (both positive and negative ones) of future technological development.

Finally, the results showed that the optimistic performance expectation (expected performance efficacy) positively affected the acceptance of service robots, while the pessimistic threat expectation negatively affected acceptance. This is consistent with the findings of earlier studies (Chatterjee et al., 2021; Huang et al., 2021; Lu et al., 2021). In other words, consumers' psychological dilemma (both positive and negative expectations) towards robotic anthropomorphism jointly determined their acceptance.

5.1. Theoretical implications

This study enhances our understanding of consumers' perceptions and expectations of future trends in service robots. Drawing upon expectancy-value theory (Pekrun, 1992; Vroom, 1964; Wigfield and Eccles, 2000), we developed a new conceptual framework to elucidate how users perceive the future anthropomorphic design of robots and how this perception impacts their acceptance of such technology. Specifically, we incorporated the concept of "paradoxical expectations" to address potentially conflicting anticipations consumers might hold concerning the performance efficacy and realistic threats associated with these robots. This is a novel extension of the expectancy-value theory, as to the best of our knowledge, no prior research has explored this aspect. Our framework factors in two primary elements: expected performance efficacy and expected realistic threats, which influence individuals' readiness to embrace service robots. Furthermore, our framework integrates individuals' levels of technology anxiety, acknowledging the role of psychological factors in shaping their expectations and evaluations of technological innovations. This is a notable extension of the expectancy-value theory, which traditionally focuses on motivation and decision-making but does not explicitly account for such personality traits an influencing factor. Overall, by encompassing expectations, values, and individual traits, our model bridges theoretical gaps, contributing to a holistic comprehension of consumer attitudes and actions towards these human-like robots.

This framework sheds light on consumers' expectancies of the values of future technological development in the case of service robots. Earlier studies focused mainly on consumers' reactions to existing humanoid robots (Chatterjee et al., 2021; Choung et al., 2022; Gursoy et al., 2019). Our findings reveal that consumer expectations of positive and negative values of future trends in service robots exhibit a greater predictive power than perceptions of the current state of service robots (Pauketat and Anthis, 2022). Therefore, by constructing a look-forwarding model that considers future factors, this study significantly contributes to the field of robot anthropomorphism research.

In addition, we advance the literature by introducing a new dimension - the human-like mind of robot anthropomorphism, to examine how the human-like appearance and mind of robots influence consumer perception. We divided robot anthropomorphism into appearance and mind aspects and investigated how human-like appearance and mind affect consumer perception. Previous studies have mostly focused on the impacts of human-like appearance or treated anthropomorphism as a single construct, neglecting the potential influence of the robotic imitation of the human mind (Choi et al., 2019; Lu et al., 2021; Puzakova and Kwak, 2017). Although some research has considered robot mind attribution from the perspectives of agency and experience (e.g., Gray et al., 2007), there has been a lack of in-depth exploration from the design perspective regarding the impact of the robotic theory of mind capacity. Our study focuses on this robotic, human-like mind capacity. Our findings suggest that appearance and mind human-likeness are separate anthropomorphic cues that influence consumers' interaction with human-like robots. In addition, the results indicate that the human-like appearance and mind affect service performance expectations, but there is unlikely to be a realistic threat prediction. This finding regarding the robotic human-like mind corroborates with conclusions of previous studies that have focused on the robot's human-like mind (Söderlund, 2022).

Moreover, this study systematically explores the paradoxical beliefs of consumers towards the technological progress of service robots that jointly determine acceptance of the technology. The widespread use and rapid development of AI and robotic technology have generated academic interest in users' mixed reactions toward the anticipated trends in service robots (Du and Xie, 2021). Most scholars view the humanization of service robots as a positive development from a utilitarian perspective (Laban and Araujo, 2019; Li and Wang, 2022), however, several studies suggest that the increased human-like appearance and mind powers of service robots may lead to human-identity blurring and resource threats (e.g., unemployment, job substitution, and resource out of control). Grounded on the expectancy-value theory (Wigfield and

Eccles, 2000), our research model considers these two aspects as the expected value and cost of the consumer's paradoxical expectations of technological progress (Scheier and Carver, 2007). Our empirical evidence demonstrates that both optimistic and pessimistic expectations jointly determine the acceptance of service robots.

Finally, this study adopts technology anxiety to explain users' expectations about the future development of service robots. Using the expectancy-value theory of anxiety (Pekrun, 1992), we have investigated the impact of this trait on consumer perceptions. Previous studies have mostly focused on technology anxiety in computers, mobile phones, self-service, and other situations (Meuter et al., 2003; Nomura, 2006; Yang & Forney, 2013). However, with the increasing prevalence of service robot technology, an examination of consumer anxiety levels toward service robots is required. Exploring this particular technology anxiety can help us gain a better understanding of how consumers with different technological inclinations may react to service robots (Meuter et al., 2003). Our results indicate that individuals with technology anxiety are generally more likely to have negative expectations and view future robots as a threat. Highly anxious consumers are more sensitive to improvements in human-like design and are more likely to experience future threats, particularly when they perceive that the future robot will have a social mind. The introduction of the personality variable of technology anxiety has enhanced our understanding of users' paradoxical psychology toward human-like service robots.

5.2. Practical implications

Service companies that use service robots can draw implications from this study's results. First, these companies should focus on enhancing customers' positive perception of the future development of anthropomorphic service robots. Future service robots will likely to become increasingly human-like with a photorealistic face or a social mind. Our findings suggest that consumers' perceptions of future service robots may affect their reactions more significantly than perceptions of the current state of the service robots. Consumer predictions of the service robot technology may be influenced by science fiction and past experiences (Aleksander, 2017; Merz et al., 2020). Therefore, service managers can promote optimistic and reasonable predictions of human-like robots among their customers, through education, demonstrations, and case studies of various robot applications in services.

Second, to promote consumer acceptance of service robots, service managers should consider ways to address users' concerns about the realistic threats posed by human-like service robots. Our research indicates that optimistic expectations regarding service robot performance efficacy can have a positive impact on acceptance, while pessimistic expectations about realistic threats can hinder acceptance. Companies should address these concerns by adopting an augmented approach, using robots to support and enhance human capabilities, rather than replacing them (McLeay et al., 2021), In addition, implementing robot technology-related corporate social responsibility strategies (Du and Xie, 2022), or focusing more on customer-centered designs rather than technology-centered designs (Reich-Stiebert et al., 2020) are likely to gain consumer acceptance.

Finally, the study suggests that companies should give more consideration to their customers who experience technological anxiety when designing and promoting their robotic products and services. One of the key findings of the study is that users who are technologically anxious react more pessimistically to the development of human-like robots. Therefore, companies should consider the design of their robots to match the technological personality of the targeted market segment. For example, if the targeted market segment is science fiction fans who have low technology anxiety, highly anthropomorphic elements embedded in robots would be beneficial (Parasuraman and Colby, 2015). Another recommendation is that companies should provide risk-free consumer engagement with robots to help reshape technologically anxious personalities (Henkens et al., 2021), such as offering adequate on-site customer support, conducting user testing, and offering educational resources such as tutorials and webinars.

5.3. Limitations and further research

This study has several limitations that suggest avenues for future research. First, the study was conducted in a Chinese context and samples were collected through online channels. Therefore, it is important to investigate if cultural differences impact perceptions and predictions for service robots in other countries. Future studies could benefit from an intercultural comparative study approach. Second, while we considered various controls to ensure internal validity, cross-sectional surveys may be relatively weak in explaining causality. Other research methods, such as experiments and longitudinal studies could be conducted to better test causal effects. Third, this study only investigated general perceptions and reactions toward service robots in a broad service context. However, the consequences may vary in specific service situations. Therefore, future research could examine the impact of robot anthropomorphism in various specific service contexts. Third, our study did not consider individual emotions interacting with service robots as a control variable. Future research could include more control variables to investigate the impact of robot anthropomorphism or other design factors on consumer attitudes and behaviors in specific service scenarios. Finally, our findings suggest that the anticipated human-like characteristics have a greater effect on perceived benefits than on perceived threats. Further research may delve into the underlying reasons for this phenomenon.

5.4. Conclusions

In conclusion, as service robots continue to evolve, it is important for service managers to take into account consumers' perceptions of future trends in service robot anthropomorphism. Our research underscores the impact of consumers' predictions of future robotic human-like features on their acceptance. Thus, it is vital to consider consumers' future predictions of service robots, particularly for those who are technologically anxious. Furthermore, it is essential to consider not only the robot's appearance but also its "mind" in promoting service robots to increase consumer acceptance.

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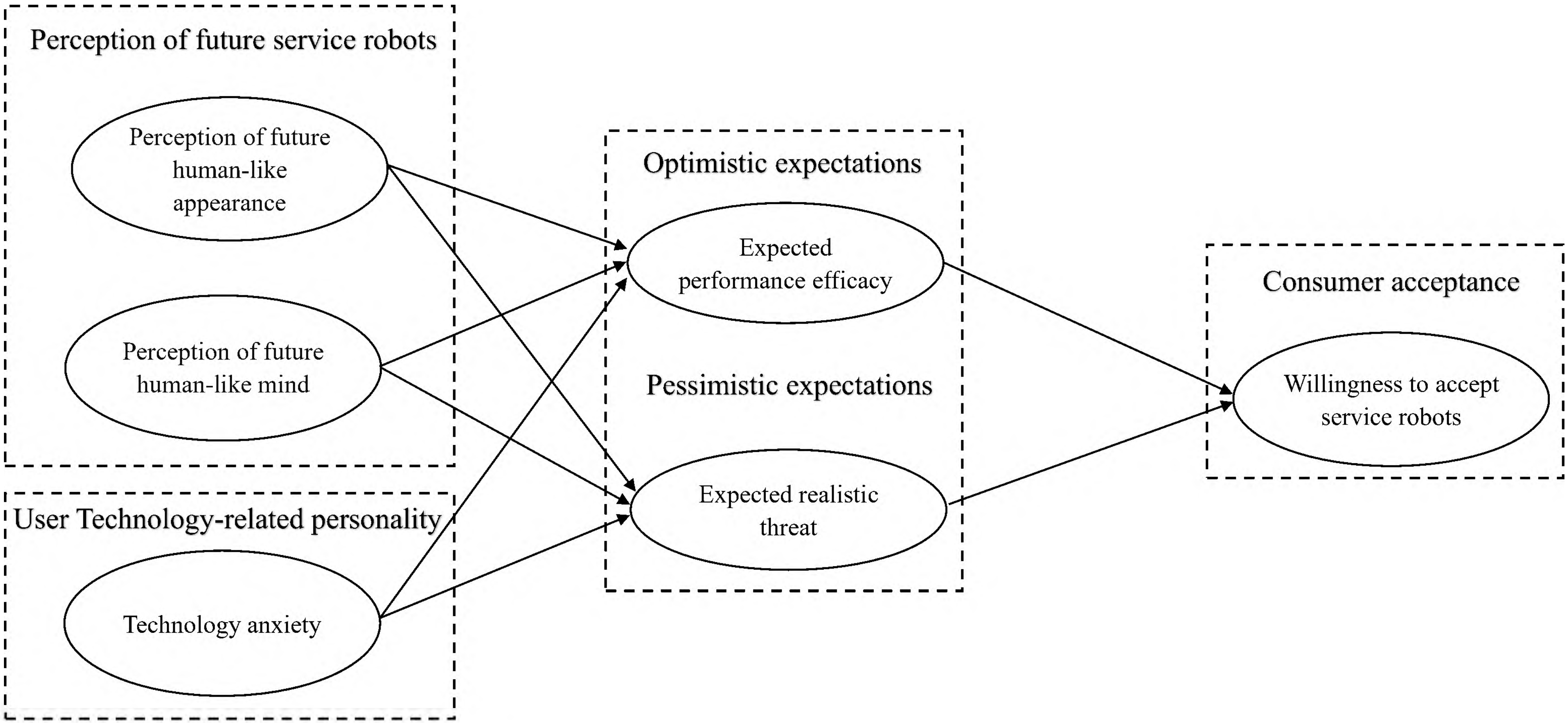


Figure 1 The research model

Note: The dashed lines and the unbold coefficients are insignificant, the solid lines and the bold coefficients are significant; $^{+} p < 0.10$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$. The specific coefficients of the control variables are omitted.

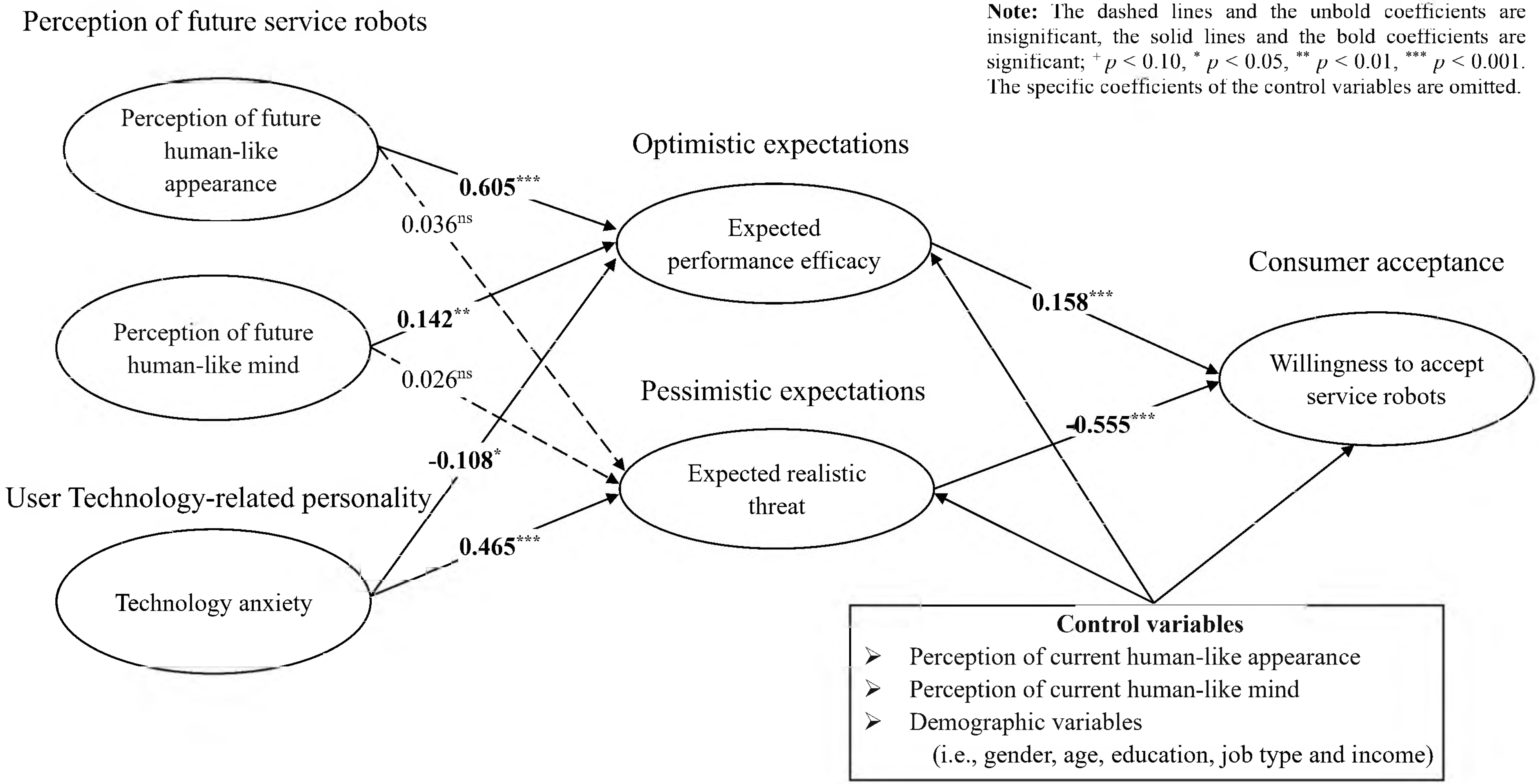


Figure 2 The path coefficients and significance of the research model

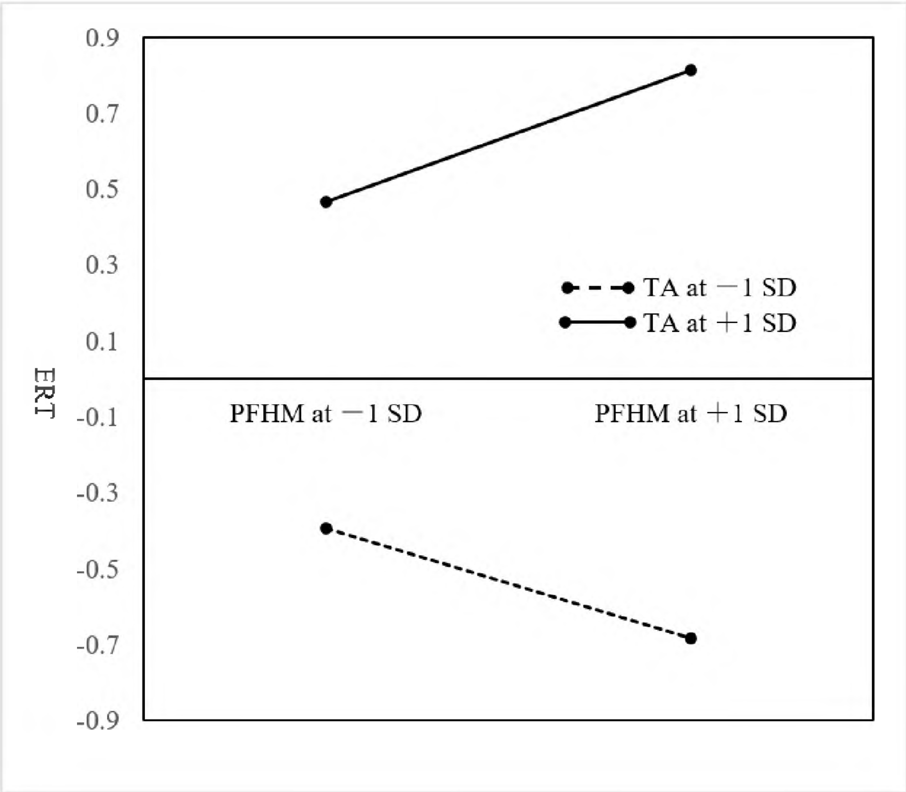


Figure 3 The post analysis of potential moderating effects of technology anxiety on perception of future robotic human-like mind and expected realistic threat.

Table 1 List of measures and item factor loadings

Variable (Source)	Label	Item	Loadings
WASR	WASR1*	Given the opportunity in the future, I will refuse to use AI service robots in a service environment.	0.865
(de Kervenoael,	WASR2*	I am not likely to accept the usage of AI service robots in the future.	0.861
2020)	WASR3*	I may intend to use AI service robots less and less in the future.	0.846
FPRHA/CPRH M	PFHA1/PCHA1	In the present/future, people (including myself) could easily mistake an AI service robot for a real person in daily life.	0.877/0.805
(Ferrari et al.,	PFHA2/ PCHA2	In the present/future, AI service robot in daily life looks like/would become more and more like a real human	0.917/0.811
2016; Pauketat and Anthis,	PFHA3/ PCHA3	In the present/future, AI service robots that people encounter in daily life appear very human-like/will become more and more human-like.	0.877/0.702
2022)	PFHA4/ PCHA4	In the present/future, people (including myself) do not/would not be able to distinguish it as a robot when encountering it in daily life.	0.887/0.788
FPRHM	PFHM1/PCHM1	In the present/future, AI service robots are/would be able to comprehend how humans perceive things.	0.898/0.876
/CPRHM	PFHM2/PCHM2	In the present/future, AI service robots are/would be able to see things from a human point of view.	0.945/0.881
(Söderlund, 2022)	PFHM3/PCH3	In the present/future, AI service robots could/would understand the mental states of humans.	0.914/0.889
TA (Henkens et al.,	TA1	(To what extent do you agree that you are such a person) I always avoid new technology because it is unfamiliar to me.	0.701
2021)	TA2	I hesitate to use most forms of new technology for fear of making mistakes I cannot correct.	0.811
	TA3	I would feel apprehensive about using new technology.	0.780
	TA4	I would feel anxious about how I should use new technology.	0.782
EPE	EPE1	Information provided by AI service robots will be more accurate with fewer human errors.	0.707
(Lu et al., 2019)	EPE2	AI-enabled service robots will be more efficient than human beings.	0.721
	EPE3	Information provided by AI service robots will be more consistent.	0.729
	EPE4	AI service robots will provide more convenient services than human beings.	0.769
	EPE5	AI service provided by service robots will be more predictable than human service.	0.781
ERT	ERT1	The increased use of AI service robots in our everyday life may lead to job loss for humans.	0.834

(Złotowski et al., 2017)	ERT2	In the long run, AI service robots will pose a direct threat to human safety.	0.882
	ERT3	In the long run, AI service robots will pose a direct threat to human well-being.	0.856
	ERT4	The development of AI service robots will take resources away from the development of humanity.	0.820

Note: * Reverse items; WASR: Willingness to accept service robots; PFHA/PCHA: Perpcetion of future/current robotic human-like appearance; PFHM/PCHM: Perpcetion of future/current robotic human-like mind; TA: Technology anxiety; EPE: Expected performance efficacy; ERT: Expected realistic threat; PCHA and PCHM are control variables.

Table 2 Means, variances, and validity analysis of variable measures

Variable	Mean	Std.	α	CR	AVE	WASR	TA	PCHA	PCHM	PFHA	PFHM	EPE	ERT
WASR	4.007	0.805	0.820	0.893	0.735	**0.857**							
TA	1.920	0.690	0.770	0.853	0.593	-0.391	**0.770**						
PCHA	3.048	1.118	0.913	0.938	0.791	0.088	-0.065	**0.890**					
PCHM	2.852	1.185	0.912	0.942	0.845	0.076	-0.011	0.667	**0.919**				
PFHA	4.224	0.612	0.781	0.859	0.605	0.148	-0.141	0.352	0.295	**0.778**			
PFHM	3.981	0.872	0.858	0.913	0.778	0.138	-0.201	0.369	0.462	0.646	**0.882**		
EPE	4.130	0.603	0.796	0.859	0.550	0.210	-0.191	0.243	0.253	0.699	0.537	**0.742**	
ERT	2.438	0.917	0.870	0.911	0.720	-0.567	0.518	-0.131	-0.123	-0.084	-0.144	-0.117	**0.848**

Note: The bold numbers in the diagonal row are square roots of average variance extracted (AVE). WASR: Willingness to accept service robots; PFHA/PCHA: Perpcetion of future/current robotic human-like appearance; PFHM/PCHM: Perpcetion of future/current robotic human-like mind; TA: Technology anxiety; EPE: Expected performance efficacy; ERT: Expected realistic threat; PCHA and PCHM are control variables.

Table 3 The results of path analysis (Bootstrapping times= 5000)

Hypothesis	The path			Coefficient β	Mean of β	SE	t-value	p-value	Remarks
H1	PFHA	→	EPE	0.605	0.605	0.060	10.129	0.000	Supported
H2	PFHM	→	EPE	0.142	0.141	0.054	2.634	0.008	Supported
H3	PFHA	→	ERT	0.030	0.030	0.055	0.541	0.588	Not supported
H4	PFHM	→	ERT	0.032	0.031	0.055	0.584	0.559	Not supported
H5	TA	→	EPE	-0.108	-0.112	0.050	2.164	0.031	Supported
H6	TA	→	ERT	0.451	0.453	0.048	9.415	0.000	Supported
H7	EPE	→	WASR	0.158	0.160	0.036	4.375	0.000	Supported
H8	ERT	→	WASR	-0.555	-0.557	0.046	12.179	0.000	Supported
Control variables									
-	PCHA	→	EPE	-0.059	-0.058	0.048	1.229	0.219	-
-	PCHM	→	EPE	0.053	0.052	0.050	1.052	0.293	-
-	PCHA	→	ERT	-0.038	-0.038	0.052	0.739	0.460	-
-	PCHM	→	ERT	-0.094	-0.095	0.055	1.698	0.090	-
-	PCHA	→	WASR	0.001	0.001	0.043	0.028	0.978	-
-	PCHM	→	WASR	-0.037	-0.038	0.048	0.759	0.448	-
-	Gender	→	EPE	0.081	0.080	0.031	2.661	0.008	-
-	Age	→	EPE	-0.041	-0.041	0.038	1.084	0.278	-
-	Education	→	EPE	-0.031	-0.031	0.037	0.849	0.396	-
-	Work	→	EPE	0.040	0.038	0.039	1.019	0.308	-
-	Income	→	EPE	0.007	0.006	0.041	0.166	0.869	-
-	Gender	→	ERT	0.014	0.014	0.041	0.341	0.733	-
-	Age	→	ERT	-0.026	-0.026	0.051	0.516	0.606	-
-	Education	→	ERT	-0.048	-0.049	0.039	1.231	0.218	-
-	Work	→	ERT	0.103	0.101	0.053	1.961	0.050	-
-	Income	→	ERT	-0.068	-0.067	0.051	1.324	0.186	-

-	Gender	→	WASR	-0.008	-0.005	0.04	0.196	0.844	-
-	Age	→	WASR	0.012	0.013	0.05	0.244	0.807	-
-	Education	→	WASR	-0.046	-0.046	0.039	1.195	0.232	-
-	Work	→	WASR	0.052	0.053	0.053	0.97	0.332	-
-	Income	→	WASR	0.05	0.049	0.044	1.133	0.257	-

Note: WASR: Willingness to accept service robots; PFHA/PCHA: Perpcetion of future/current robotic human-like appearance; PFHM/PCHM: Perpcetion of future/current robotic human-like mind; TA: Technology anxiety; EPE: Expected performance efficacy; ERT: Expected realistic threat; PCHA, PCHM and demographic variables are control variables.

Appendix

Survey instruction

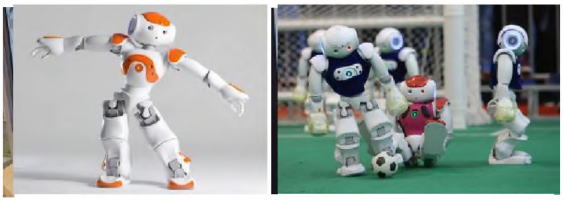
Please take the time to read the following introduction about service robots with artificial intelligence carefully.

AI robots were initially introduced in science fiction literature, and later, popularized in movies featuring renowned robot characters such as the T-800 in “Terminator,” WALL-E in “WALL-E,” and Silly Strong in “From Vegas to Macau.” With the rapid development of AI service robot technology, these robots are being increasingly deployed across various sectors of the service industry. Service robots of various types and degrees of interactivity with the public are being utilized to complete service processes. Furthermore, robotics companies are currently testing higher-intelligence service robots for future deployment. Examples of service robots can be found in restaurants, where they are used to prepare and deliver dishes. In hotels, service robots are programmed to engage in conversations with guests and assist them with check-in and luggage transportation. Home service robots have been developed to provide care and health services to the elderly, while virtual social robots offer companionship and chat services. Below are pictures along with their corresponding text showcasing various applications of service robots

[*Please note: With the advancement of AI, robots gained autonomy and adaptability, leading to their increased use in the service industries (Marinova et al., 2017; Wirtz, 2018; Jörling et al., 2019), including embodied robots that can move around in a physical environment and disembodied robots with virtual human-like features on an electronic screen (Wirtz, 2018; Jörling et al., 2019).]

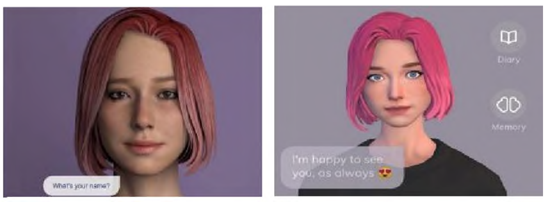
(1) A robot delivers (left) and prepares (right) food at a restaurant

(2) Peppa robot provides airport enquiry service (left) and greeting service (right)



(4) NAO robots show public entertainment services, dancing (left) and playing football

(5) Grace Robot provides care as a health care worker



(6) Replica virtual robot chats with users as a social companion

Once you have finished reading, please take a few moments to share your honest thoughts by participating in the provided survey.