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UNDERSTANDING PRE-INTERACTION RESPONSE TO HUMANOID ROBOTS: A VIEW OF COMFORT WITH ROBOTS

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UNDERSTANDING PRE-INTERACTION RESPONSE TO HUMANOID ROBOTS: A VIEW OF COMFORT WITH ROBOTS

Research Paper

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Abstract

Despite the growing body of research exploring consumer responses to robotics, the existing comprehension of this topic locates mainly on consumers' post-interaction reactions to robots based on technology-related and service-related views, leaving the complexity of pre-interaction uninvestigated. Motivated by a scarcity of knowledge on consumers' reactions to service robots before their actual interaction, this study disentangles how perceived comfort with robots, as a pre-interaction perception triggered by robot anthropomorphism, penetrates customers' implicit social decision-making and affects customer responses. By a large-scale scenario-based experiment, this study allocated a fine-grained spectrum of anthropomorphism and cartographically delineated the Uncanny Valley-resemblance effect of anthropomorphism degree on comfort with robots and trust. Furthermore, our study reveals the role of human-robot trust in mediating the relationship between comfort with robots and usage intention. The findings provide tools for future studies into understanding pre-interaction responses from social-psychological elements that could inform the design of socially competent robots.

Keywords: Comfort with robots, Pre-interaction, Human-robot trust, Humanoid robot.

1 Introduction

The advancement of artificial intelligence (AI) and robotics allows robots to not only be bound up in the technological environments but also penetrate our social sphere and interact with users in more casual intuitive approaches (Mathur and Reichling, 2016; Merkle, 2021). Against this backdrop, an increasing amount of professional robots have proliferated forward to service sectors (Crook, 2014; Osawa *et al.*, 2017; Tussyadiaha and Parkb, 2018) or even replacing human staff in service delivery processes (Buhalis *et al.*, 2019; Ho *et al.*, 2020; Larivière *et al.*, 2017). With the value of the service robotics market at 23.6 billion USD in 2020, the latest statistics forecast a growth rate at a compound annual growth rate of 44.9% over the period from 2021 to 2026 in the global service robot market (MordorIntellingence, 2021).

With the proliferation of the robot workforce in service sectors, we cannot emphasize too much the importance of customer adoption of robots, which is closely linked to customer response to robots. Deploying robots in service sectors marks a transition from customer-producer interaction to human-robot interaction (HRI). By incorporating robots into service delivery, HRI exhibits several new features distinct from user interaction with conventional service digital agents. In particular, users tend to develop cognitive or emotional perceptions of a digital agent after using it. However, users' perceptions of robots (hereafter referred to as robots with physical presence) are formed regardless of their functionality before interacting with them by observing their physical presence (e.g., Eveleth, 2013; Haring *et al.*, 2013; Koay *et al.*, 2006). This represents that customer responses to robots start to shape before interacting with a robot, dubbed *pre-interaction*. Such responses from observing robots' physical presence are unique for robots in comparison to conventional digital service agents that are intangible in nature.

Among all the robot attributes related to physical presence, anthropomorphism, or humanoid appearance, can be the one that attracts the most research and managerial interests. Still at the embryonic development stage, humanoid robots cannot imitate human behavior perfectly, which is currently the central problem in designing socially interactive robots (Mathur and Reichling, 2016). Whereas human reactions to imperfect humanoid robots are complicated, Uncanny Valley Hypothesis (UVH) is one of the most widely applied theoretical lenses to interpret the relationship between robot anthropomorphism and human emotions (Blut *et al.*, 2021; Mathur and Reichling, 2016), such as likeability/affinity (Amelia *et al.*, 2022; Blut *et al.*, 2021; Seymour *et al.*, 2021) and warmth (Choi et al., 2021; Yoganathan et al., 2021). Among all the discussed emotional variables that are directly linked to anthropomorphism in past research, likeability can be the one paid the most attention to (Mathur and Reichling, 2016).

In this study, we attempt to employ the comfort theory to explain users' responses from observing service robots. We argue that a sufficient level of comfort with robots is critical before an adoption decision. Comfort seeking is a behavior of human nature penetrated from the moment of birth to death (Slater, 1985; Spake *et al.*, 2003). Individual comfort with a certain object is an overall human feeling *by taking the object's appearance, behavior, and distance into account* (Ball *et al.*, 2015; Tang and Cao, 2012). In other words, comfort is a multidimensional construct comprising physical comfort (e.g., pain alleviation), physiological comfort (e.g., involuntary reactions to environmental discomfort like hair standing on end by seeing a zombie), psychological comfort (e.g., peace of mind) (Slater, 1985; Spake *et al.*, 2003). The object that an individual has a feeling of comfort with can be pluralistic, including but not limited to a person (e.g., service provider), technology (e.g., software and laptop), relationship (e.g., intimate relationship), etc. Comfort theory has been extensively applied to study humans' responses and behaviors in, for example, healthcare (Kolcaba, 2003) and service relationship management (Spake *et al.*, 2003). Compared to emotional reactions such as likeability, comfort is a broader concept reflecting a holistic positive feeling that involves observing, touching, and interacting with specific objects and/or environments. In the robotic service (*r*-service) context, service robots are deployed as service providers. This enables consumers to shape comfort/discomfort feeling by observing, approaching, touching, or interacting with the robot. In this vein, perceived comfort appears to be a more appropriate measure when evaluating a robot approaching a user to provide a service. Despite that the significant role of consumer comfort in service relationships has been highlighted (Spake *et al.*, 2003), little is known about consumer comfort in *r*-service. Furthermore, there is a paucity of knowledge regarding how anthropomorphism, a typical robot-design attribute, affects consumers' comfort with robots, and so is the influence of comfort with robots on social decision-making and technology adoption decisions. Thus, this study strives to answer the following two research questions (RQ):

RQ1*:* How does anthropomorphism affect comfort with robots and social decision-making?

RQ2*:* How does comfort with robots affect humans' social decision-making and adoption decisions?

To answer the research questions, a scenario-based experiment at a large scale was conducted on 3893 respondents. Analysis results attest to the distinct role played by anthropomorphism in affecting comfort with robots and trust. The mediating effect of trust was corroborated by the relationship between comfort with robots and usage intention. Findings from this study make threefold contributions to research. First, this study illuminates the pre-interaction responses of consumers to service robots by uncovering the curvilinear relationship between anthropomorphism and comfort with robots/trust. In doing so, we extend previous scholarly work scrutinizing consumer responses caused by the physical presence of service robots. Second, this study is among the first to apply comfort theory to comprehend individual implicit social decision-making, delivering a novel theoretical lens worth considering in future inquiries into AI robots. Third, by shedding light on the role of trust in mediating the effect of comfort with robots on usage intention, we advance contemporary knowledge on how consumers respond to service robots based on a nuanced understanding of the pre-interaction underlying mechanism. In addition, findings from this study contribute to practice in two ways. First, given the popularity of robotics in service sectors, we offer recommendations for how practitioners can adjust their design strategies to avoid the UV effect. Second, we advocate for improving human-robot trust as a strategy to enhance consumers' usage intention and the success of service robot deployment.

2 Literature review and theoretical basis

2.1 Customer response to robot anthropomorphism

Customer responses to *r*-services or service robots have progressively been a heated theme of robotics in IS field. The current literature on customer response to robots emphasizes the influence of robot-design components, from robot appearance to functions. In particular, *anthropomorphism* can be one of the most frequently discussed terminologies in the existing literature. Drawing upon UVH (Mori, 1970), anthropomorphism is conceptualized as the extent to of robotics having human characteristics of either physical appearance or psychological features (Lu *et al.*, 2019). Similar constructs, e.g., humanness (Amelia *et al.*, 2022; Fernandes and Oliveira, 2021; Mele *et al.*, 2020), humanoid (Choi *et al.*, 2021; Qiu and Benbasat, 2009), human-like (Lu *et al.*, 2021), and social presence (Fernandes and Oliveira, 2021; Mele *et al.*, 2020; Romero and Lado, 2021), have also been investigated by previous studies. Table 1 presents a summary of critical studies pertinent to robot anthropomorphism.

Anthropomorphism has been identified as significant in customer acceptance and intention to (re)use robots, but mixed results have been shown in past studies. On the one hand, previous evidence suggests that anthropomorphism can positively affect customer attitudes, willingness, and acceptance/adoption of robots. For instance, Chuah et al. (2021) validated the significance of human-likeness in achieving consumers' intention to use service robots. Tussyadiaha and Parkb (2018) show that anthropomorphism positively affects the adoption intention of hotel service robots. Likewise, Chi et al. (2022) demonstrated that anthropomorphism positively impacts users' willingness to use AI devices through perceived performance expectancy, perceived effort expectancy, and emotion. On the other hand, several studies endorse a negative effect of anthropomorphism on customer acceptance/adoption of robots. Concretely, Lu et al. (2019) found that anthropomorphism negatively affected the willingness to use service robots. Similarly, the work by Huang et al. (2021) revealed that anthropomorphism in terms of robot appearance could strengthen the negative effect of negative attitudes toward robots on usage intention. Interestingly, a few studies reported a nonlinear effect of robot anthropomorphism on consumers' privacy concerns (Xie and Lei, 2022) and trust (Zhang *et al.*, 2021), thereby affecting the intention to use service robots.

Notably, whereas a growing body of literature on customer responses to robotics has appeared in IS field, most of them investigate customers' emotional responses during or after HRI. Very little is known about people's pre-interaction perceptions. This is somewhat surprising because understanding individual pre-interaction perceptions of service robots is of great importance in end-user acceptance of robotics and the success of HRI implementation (Duffy, 2003; Fong *et al.*, 1974; Groom and Nass, 2007). Furthermore, past studies have shown mixed results regarding the effect of anthropomorphism on customer responses. Numerous studies attributed higher adoption intention to the influence of robot anthropomorphism (Chi *et al.*, 2022; Tussyadiaha and Parkb, 2018). However, several studies reported a negative impact of anthropomorphism on the wiliness to use a robot (Lu et al., 2019) or even an insignificant relationship between perceived humanness and acceptance of digital voice assistants (Fernandes and Oliveira, 2021). In this light, echoing UVH, a plausible inference is that the effect of anthropomorphism on customer responses is non-linear. Alternatively, several possible mediators may exist to alter the overall relationship between anthropomorphism and customer intention to use a robot. Such concerns motivate the present study.

2.2 Uncanny valley effect

"*In climbing toward the goal of making robots appear human, our affinity for them increases until we come to a valley*" (Mori, 1970, p. 34), which is named the uncanny valley (UV), as shown in Figure 1. The UV effect hypothesizes a non-linear relationship between the degree of a robot's human resemblance and the emotional response to such a robot. Specifically, this conceptualization suggests that the humanoid robot, with imperfect human resemblance, provokes uncanny or weirdly familiar feelings of eeriness and even revulsion in the observer. Prominently, Mathur and Reichling (2016) empirically exhibit the existence of the UV effect in subjects' reactions, i.e., emotion and likability, to android robots and its penetration in people's social behaviors related to human-robot trust.

Study	Theoretical grounding	Agents of anthropomorphism					Responses to robot anthropomorphism																										Explained variables				
		Anthropomorphism	Robot appearance	Humanoid embodiment	Humanness	Humanity	Trust	Emotion	Usefulness	Performance expectancy	Effort expectancy	Utilitarian value	Ease of use	Likeability	Rapport	Enjoyment	Competence	Warmth	Affect	Performance ambiguity	Prevention efficacy	Social presence	Safety	Intelligence	Animacy	Hedonic dimensions	Psychological comfort	User satisfaction	Psychological risk	Service quality	Blame attribution	Privacy concerns	willingness	Attitudes	Satisfaction	Acceptance	Intention to (re)use
Liu *et al.* (2022)	—		√				√																														√
Chi *et al.* (2022)	—	√						√		√	√																						√				√
Amelia *et al.*(2022)	UTAUT				√									√		√											√									√	
Xie & Lei (2022)	PCT	√																														√					√
Blut *et al.* (2021)	UVT, SPT, TTFT	√					√		√				√	√	√				√			√	√	√	√			√									√
Choi *et al.* (2021)	SET, MSET			√														√																	√		√
Chuah *et al.* (2021)	CT	√																																			√
Fernandes and Oliveira (2021)	UVT, UTAUT, RT				√																															√	
Huang *et al.* (2021)	UVT	√																																			√
Li and Wang (2022)	TAM	√							√																									√			√
Lu *et al.* (2021)	UVT, AT	√																															√				
Odekerken-Schröder *et al.* (2022)	UVT, MET	√										√														√											√
Romero and Lado (2021)	UVT	√																			√													√			√
Yoganathan *et al.* (2021)	SPT, SCT			√													√	√		√									√	√			√				√
Zhang, Meng, *et al.* (2021)	SPT, SoRT, CDVT					√	√																													√	
Fan *et al.* (2020)	CPT, SReT	√																													√				√		
Lehmann *et al.* (2020)	UTAUT		√																															√			
Lin *et al.* (2020)	UVT, AIDUATF	√						√		√	√																						√				√
Mele *et al.* (2020)	TAM				√		√	√				√	√		√																						√
Roy *et al.*(2021)	CAT	√						√		√	√																						√				√
Gursoy *et al.* (2019)	CAT, CDT	√						√		√	√																						√				√
Lu *et al.* (2019)	UTAUT	√																															√				
Moussawi & Koufaris (2019)	UMITC	√							√																			√									√
Tussyadiaha & Parkb (2018)	—	√																																			√
Qiu and Benbasat (2009)	SRT			√			√		√							√						√															√

Note: UTAUT = unified theory of acceptance and use of technology; PCT = Privacy calculus theory; SPT = Social presence theory; TTFT = Task–technology fit theory; UVT = Uncanny valley theory; SET = Social exchange theory; MCT = Mental accounting theory; CT = Complexity theory; RT = Role theory; TAM = Technology acceptance model; AT = Appraisal theory; MET = Media equation theory; SCT = Social cognitive theory; SoRT = Social reaction theory; CDVT = Customer delivered value theory; CPT = customer participation theory; SReT = Social response theory; AIDUATF = AI devices use acceptance theoretical framework; CAT = Cognitive appraisal theory; CDT = Cognitive dissonance theory; UMITC = Unified model of IT continuance; SRT = Social Relationship Theory.

Table 1. Summary of critical literature on customer response to robot anthropomorphism.

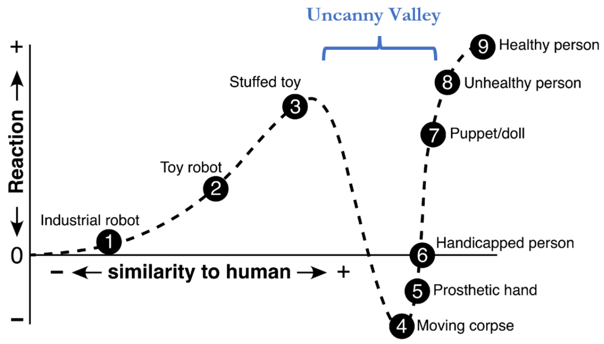

Figure 1. The Uncanny Valley Hypothesis, adapted from Mori (1970).

2.3 Comfort theory

Comfort theory originated in and for nursing. Comfort is determined by a combination of physical and psychological factors (Ayachi *et al.*, 2015), which undertakes many meanings and connotations much more than ease or relief of discomfort (Juhas-Davis, 2015). Holistic comfort includes such multiple aspects as physical, psychospiritual, sociocultural, and environmental needs (Wilson and Kolcaba, 2004). Comfort refers to "*the immediate state of being strengthened through having the human needs for relief, ease, and transcendence (types of comfort) addressed physically, psychospiritually, socioculturally, and environmentally*" (contexts in which comfort is experienced) (Kolcaba, 2003, p. 251). From a perspective of human-environment relation, comfort is defined as a state of harmony between humans and the environment in three dimensions: "*physiological, psychological and physical*" (Slater, 1985). That is to say, comfort with robots can be understood as a state of harmony between a human subject and an observed/interacted robot.

In HRI, comfort level might better reflect the expectations and prior experiences that influence social responses to social behavior. Being conceptualized as the opposite of anxiety (Daniels, 2000), the relief of comfort with a service provider triggers mental benefits to consumers by reducing anxiety and unease (Chen and Popovich, 2003; Spake *et al.*, 2003). Consumer comfort in building service relationships has been well documented; consumer comfort with service providers is ascertained as a key dimension of the overall service experience quality (Ardelet *et al.*, 2022; Meyer *et al.*, 2017; Spake *et al.*, 2003). For instance, consumers' psychological comfort with service providers contributes to higher satisfaction, trust, and commitment (Spake *et al.*, 2003). Consumer comfort in service relationships positively influences perceived service quality (Ardelet *et al.*, 2022). Nevertheless, despite that a few studies mentioned the significance of comfort with robots during HRI in establishing trust (Hancock *et al.*, 2021) and producing more positive responses to social behavior (Lubold *et al.*, 2019), the role of consumer comfort with robots in *r*-service relationships has virtually unexplored in IS domain.

Based on the comfort theory, the feeling and perceived degree of comfort depend on the surroundings, the situation, and the individual (Ball *et al.*, 2015; Tang and Cao, 2012). The robot, acting as an environmental element that people observe and interact with, will directly affect humans' comfort feelings. Furthermore, comfort with robots might further impact subjects' perceptions and responses to the robot. Individuals with discomfort with robots might be more cautious and more prone to anxiety and stress, with no expectations regarding an agent's social behavior. As such, it would be beneficial and interesting to unravel how robot anthropomorphism influences the comfort level of humans and how humans react to the robot, for example, trust in the robot and are willing to try the *r*-service.

3 Hypothesis development and research framework

Anthropomorphism, as a design element of robots, can create a sense of comfort in end-users (May *et al.*, 2017; Sanders *et al.*, 2011). Anthropomorphism can be conceptualized as a "*tendency to animate non-human and/or inanimate objects*" (May et al., 2017, p. 169), which has spurred the active interest of researchers in robot research (Blut et al., 2021; Chi et al., 2022; Lu et al., 2021). When individuals anthropomorphize a non-human robotic agent, they inevitably and involuntarily attribute human-like qualities and characteristics to the robot (Epley *et al.*, 2007; May *et al.*, 2017). Arguably, the tendency of anthropomorphizing robotics allows users to understand and use the agent better because anthropomorphizing robotic agents may create social presence and social connections, thus making users feel more comfortable around the robot (Epley *et al.*, 2007; May *et al.*, 2017; Sanders *et al.*, 2011).

Nevertheless, a more recent consideration in theorizing HRI based on UVH assumes a non-linear relationship between the degree of human-likeness in robots and perceived comfort by observers (Mathur *et al.*, 2020; Plaks *et al.*, 2022; Yam *et al.*, 2021). Specifically, people are more likely to feel more comfortable with robots that look distinctly different from humans than robots that look somewhat similar to humans (Plaks *et al.*, 2022). Just like affinity endorsed by UVH (Mori, 1970), an individual's comfort with a humanoid robot could suddenly shift from comfort to malaise due to eerieness as it approached but failed to acquire a lifelike appearance. Before a certain threshold of human likeness, observers' comfort with a robot would go up with the human-like level. However, their feelings of comfort would abruptly fall to the "*UV bottom*" at the threshold point. This is due to the fact that humanoid robots are unable to be ideally granted the whole human nature (Castelo *et al.*, 2018). Then, beyond the threshold, robots might be seen as entities possessing a certain degree of humanity, and further addition of human-likeness might increase the comfort level. Thus, we posit that:

H1: There is a *UV-resemblance* curvilinear relationship between anthropomorphism and perceived comfort with robots.

Anthropomorphism affects the human-robot trust (Blut *et al.*, 2021; Hancock *et al.*, 2021; Plaks *et al.*, 2022). Notably, previous studies convey mixed results concerning the effect of anthropomorphism on trust. Most past studies support that the anthropomorphism of robots helps establish and increase trust (Blut *et al.*, 2021; van Pinxteren *et al.*, 2019; de Visser *et al.*, 2016). When human-like qualities are attributed to robots, people are prone to believe that the robot is capable of performing the intended functions, representing higher trust in the competence of more human-like robots in service delivery. However, some studies deem a negative or even insignificant relationship between anthropomorphism and trust (Blut et al., 2021; Erebak and Turgut, 2019; Hancock, Billings, Schaefer, et al., 2011). Moreover, it is worth mentioning that a non-linear between anthropomorphism and trust has been evidenced in a few studies (Mathur and Reichling, 2016; Zhang *et al.*, 2021). As shown by Zhang *et al.* (2021), an inverted-U relationship exists between the perceived humanity of AI virtual robots and users' trust. Given the mixed findings in past studies, it is conceivable that the relation between robot anthropomorphism and users' trust in the robot is curvilinear. Drawing upon UVH, we posit that:

H2: There is a *UV-resemblance* curvilinear relationship between anthropomorphism and consumers' trust in robots.

While it is widely acknowledged that trust plays a vital role in facilitating HRI, the antecedents that influence trust itself leave, to a large degree, to be further investigated, in particular before interaction with robots. Therefore, identifying potential antecedents of trust is the first and crucial step in the subsequent calibration of trust in HRI. Comfort with robots is alluded to correlated with trust in robots in past research (Evers *et al.*, 2008; Hancock *et al.*, 2021; Sanders *et al.*, 2011). Both warmth-oriented and competence-oriented features affect users' trust in service robots (Liu *et al.*, 2022; Zhang *et al.*, 2021), whereas trust encompasses cognitive and affective trust (Wang *et al.*, 2016). Cognitive trust captures consumers' confidence in a robot's competence in service delivery, and affective trust represents consumers' belief that the robot cares for the consumer (Wang *et al.*, 2016). Before actual interaction with robots, consumers' trust tends to be dominated by perceptions generated by observing the robot's presence rather than utilitarian values resulting from the evaluation of HRI. A consumer's perceived comfort with a robot reflects the level of harmony state between the consumer and the robot (Slater, 1985). Consumers may see the robot that they perceive as more comfortable be more appealing and develop the belief that the robot would be pleasurable to interact with. As an emotional reaction that emerges directly from observing service robots, increasing comfort with a robot may generate higher consumer trust and, thereby, a higher likelihood to use the robot. Therefore, we hypothesize that:

H3: Consumers' perceived comfort with a robot has a positive effect on their trust in the robot.

H4: Consumers' perceived comfort with a robot has a positive effect on their usage intention.

Trust is a factor of high importance to be taken into account in the HRI environment to explain and predict consumer adoption of robots (Alaiad and Zhou, 2014; Liu *et al.*, 2022; Zhang *et al.*, 2021). Trust in technology is known as an indicator of a positive attitude or belief in the reliability, dependability, and confidence that the technology (e.g., service robots) can fulfill forth-set obligations and help users achieve desired goals (Alaiad and Zhou, 2014; Tussyadiah *et al.*, 2020). The critical role of trust in facilitating the intention to use service robots has been acknowledged and emphasized in previous studies (Blut *et al.*, 2021; Liu *et al.*, 2022; Mele *et al.*, 2020). For instance, Park (2020) verified a formative model of multifaceted trust in service robots and empirically confirmed that trust beliefs in robots strongly contribute to consumers' intention to use the robots. Likewise, Liu *et al.* (2022) endorsed that consumers' perception of robot appearance (warm or competent) significantly drives their trust in the robots, which further affects their intention to use the robot in tourism service settings. Trust is essential to activating *r*-services because of its linkage to the needs of individuals to control, at least perceive that they are capable of understanding the social circumstance where they interact (Alaiad and Zhou, 2014). In this vein, trust in robots indicates that users believe the robot with the capability to deliver the required service task. While the current literature mainly focuses on the effect of trust on adoption decisions based on evaluating the functionality of robots after HRI, this study argues that consumers' trust belief before HRI would also boost usage intention. Only when a consumer develops a belief that the service robot is trustworthy and capable of performing its intended function, can the consumer expect the robot to meet their needs to perform specific service tasks. Thus, we posit that:

H5: Consumers' trust has a positive effect on consumers' intentions to use humanoid service robots.

Based on the above-proposed hypotheses, a research framework is established, as shown in Figure 2.

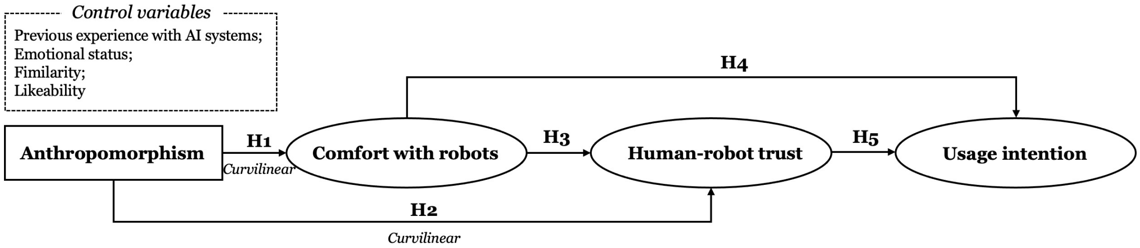

Figure 2. Research framework.

4 Methodology

The empirical data was obtained via a scenario-based experiment, widely utilized in IS research by manipulating various conditions for specific variables to represent a research context and/or simulate response tasks (e.g., Barlow *et al.*, 2018; Sheng *et al.*, 2008). In a scenario-based experiment, the respondents are required to report their perceptions via a questionnaire after going through assigned pre-designed scenarios containing experimental treatments set forth.

4.1 Research design

Following Mathur and Reichling (2016), a similar image sample pool comprising 80 real-world robot images has been used in the present study, co-opting most of their robot images (73 out of 80). Unfortunately, 7 robot images still needed to be obtained. We had 7 similar robot images retrieved online, strictly obeying the criteria developed by Mathur and Reichling (2016). To determine the rank in terms of the mechano-humanness level of the robots, we convened a panel of four judges to assess the 7 new images. All four judges were doctoral students majoring in IS or management studies who had previous experiences using service robots. The assessment panel was first asked to rank the 7 images individually and explain the reached rank. Then, the four participants jointly conducted a round table discussion regarding the rank differences to achieve a consensus on the order of all 80 images. In so doing, the image sample pool is created, illustrated in Figure 3. The robot anthropomorphism degree can be quantified. Furthermore, the sample size and diversity in anthropomorphism are fulfilled to enable a fine-grained statistical analysis of the impact of anthropomorphism on observers' perceptions.

Figure 3. The sample pool ordered and presented according to anthropomorphism score ascending

4.2 Measures

Comfort with robots has been attracting increasing research interest in recent years. However, this term is seldom systematically drawn into robotic research in IS realm despite being slightly touched upon in past studies (Ball *et al.*, 2015). Our study developed a comfort with robots measurement following the scheme developed by Moore and Benbasat (1991)[1]. We created two different measures of comfort with robots: *formative comfort with robots* encompasses psychological and physiological comfort, and *holistic comfort with robots* represents the overall comfort level with a robot. Measurements of trust (Ahmad, 2009; Etemad-Sajadi, 2016; Gefen, 2002; Nunamaker *et al.*, 2011), usage intention (Qiu and Benbasat, 2009), likeability (Nunamaker et al., 2011; Seymour et al., 2021), and familiarity (Chi *et al.*, 2021) were from previous literature. A pilot study with 60 participants was performed to enhance the reliability and validity of the constructs in the questionnaire[2].

4.3 Experiment implementation and data collection

The data was collected via Amazon Mechanical Turk (AMTurk), a widely-used crowdsourcing site where workers perform required tasks online in return for payment. The participants were recruited between October 2021 and May 2022 and received about 1.6 USD as remuneration upon completing the experiment. Figure 4 illustrates the experimental procedure.

After browsing the introduction of the study and granting consent to participate in the experiment, respondents were asked about their previous experience using AI-based systems. Those without any AI-based system experience were excluded from this study. Then, participants were required to conduct a qualification check by singling out one listed picture with a higher level of anthropomorphic appearance. The surviving participants were asked to report their demography and look through the thumbnails that presented all 80 robot faces (unordered). Afterward, they were randomly assigned one image and filled in the questionnaire according to the given image. Six attention-check questions were implemented in the questionnaire, which enabled to drop off of participants if they failed to pass any stringent attention checks. After screening inattentive records, 3,893 valid records remain; each of the 80 images got at least 44 responses, averaging 48.7 responses. Table 2 presents the participants' demography.

[1] Please see Appendix A of the online supplementary materials for the instrument development process.
[2] Please see Appendix B of the online supplementary materials for the final questionnaire.

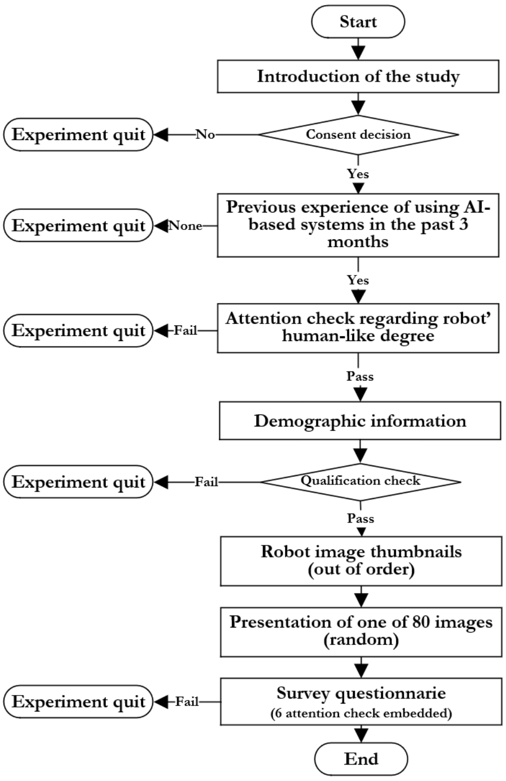

Figure 4. Experimental procedure.

Demography	Categories	Frequency
Times of using AI-based systems	1-3 times	856
	4-6 times	1,024
	7-9 times	414
	More than 9 times	1,599
Gender	Male	2,359
	Female	1,495
	Others	3
	Prefer not to say	36
Age	Under 18 years old	1
	18-25 years old	119
	26-35 years old	1,707
	36-45 years old	1,204
	46-55 years old	463
	56-65 years old	245
	66 or above	87
	Prefer not to say	67
Education	Less than high school	9
	High school	524
	Bachelor's degree	2,591
	Master's degree or higher	700
	Prefer not to say	69
Annual household income	Less than $25,000	843
	$25,000 -$50,000	1,143
	$50,000 -$100,000	1,134
	$100,000 -$200,000	628
	More than $200,000	84
	Prefer not to say	61

Table 2. Demography of participants.

5 Data analysis and results

The structural equation modeling (SEM) technique via SmartPLS was mainly used to test the research model. Following the recommended procedure (Hulland, 2015), we first assessed the measurement model by examining the reliability and validity of all constructs; then, we verified the structural model by testing the effect pathways among the constructs, as well as their significance levels.

5.1 Measurement model

Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were used to assess the internal consistency of the latent variables (Fornell and Larcker, 1981). In our study (see Table 3), the values of Cronbach's alpha, CR, and AVE for all constructs were above their recommended thresholds of 0.7, 0.7, and 0.5, respectively, confirming sufficient internal consistency.

Constructs	Minimal cross-loading	Cronbach's Alpha	CR	AVE	1	2	3	4	5	6	7	8	9	10
1. ANT	1.000	1.000	1.000	1.000	**1.000**									
2. EMO	1.000	1.000	1.000	1.000	0.400	**1.000**								
3. LIK	0.802	0.946	0.958	0.790	0.490	0.668	**0.889**							
4. PE	1.000	1.000	1.000	1.000	-0.152	-0.087	-0.147	**1.000**						
5. TRU	0.908	0.959	0.968	0.859	0.396	0.553	0.803	-0.123	**0.927**					
6. UI	0.969	0.974	0.983	0.950	0.272	0.386	0.665	-0.128	0.707	**0.975**				
7. HC	0.915	0.968	0.974	0.862	0.360	0.538	0.806	-0.083	0.784	0.732	**0.929**			
8. FAM	0.927	0.940	0.961	0.892	0.230	0.233	0.421	-0.050	0.388	0.379	0.363	**0.945**		
9. PHC	0.872	0.974	0.978	0.864	-0.174	-0.070	-0.149	0.391	-0.091	-0.082	0.041	-0.461	**0.929**	
10. PSC	0.897	0.973	0.977	0.843	0.370	0.562	0.836	-0.062	0.789	0.695	0.900	0.353	0.023	**0.918**

Note: (1) ANT = Anthropomorphism degree; EMO = Emotional status; LIK = Likeability; PE = Previous experiencen with AI systems; TRU = Trust; UI = Usage intention; HC = Holistic comfort; FAM = Familiarty; PHC = Physiological comfort; PSC = Psychological comfort. (2) The bolded numbers in the diagonal row are the square roots of AVEs. ANT, EMO, and PE are single-item variables, so their AVEs are 1.

Table 3. Reliability and Correlation matrix.

The convergent and discriminant validity was examined by assessing the factor loadings and cross-loadings (Cook and Campbell, 1979). As shown in Table 3, the cross-loadings on each construct were above 0.70 and also higher than factor loadings on all the other constructs, indicating excellent convergent and discriminant validity. Furthermore, the square root of the AVE for each construct was above their corresponding correlation coefficients, double confirming fair discriminant validity for these constructs (Bock *et al.*, 2005).

The second-order formative construct—*comfort with robots*—was measured by two first-order reflective variables, i.e., physiological and psychological comfort. In line with Petter et al. (2007), the formative construct was assessed by examining its weights, loadings, and variance inflation factors (VIF). As demonstrated in Table 4, the weights for physiological comfort and psychological comfort are highly significant. Moreover, multicollinearity among the first-order reflective variables was examined by assessing the values of VIF. As the VIFs were lower than 3.0, multicollinearity did not significantly affect the analysis results (Neter *et al.*, 1996).

First-order reflective variables	Weight	*T*-statistics	Variance inflation factors (VIF)
Physiological comfort	0.474^{***}	5.893	1.725
Psychological comfort	0.916^{***}	23.320	1.811
Note: ***means $p < 0.001$			

Table 4. Weights and s-statistics of the second-ordered formative construct.

5.2 Hypotheses testing

5.2.1 The UV-resemblance curvilinear relation between anthropomorphism and comfort with robots/trust

The participants were required to rate the assigned robot face by answering the question, "*This robot is from very machine-like (−100) to very human-like (100)*". In addition, they were also right then asked to report their emotion by answering "*How much positive or negative emotion is this robot face showing?*" from *very negative (−100)* to *very positive (100).* By doing this, we could largely isolate the interference of emotions on the results in the following analysis.

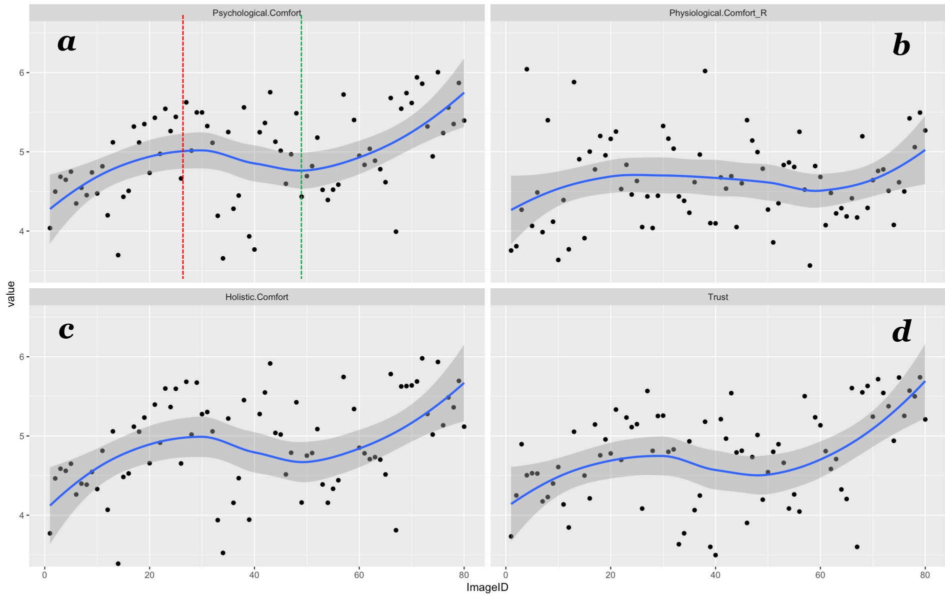

Figure 5. Effect of anthropomorphism on psychological comfort (a), physiological comfort (b), holistic comfort (c), and trust(d)

By performing the analysis in *R*, we first confirmed the effectiveness of the manipulation on anthropomorphism of all 80 face stimuli. Although the trend line of the perceived anthropomorphism rated by the participants can not perfectly match the 80 pre-ranked images, their correlation is significant ($r = 0.927^{***}$, method = Pearson). This represents that our manipulation of robot anthropomorphism is effective. To depict the relation between robot anthropomorphism level and comfort with the robot, we further draw the relationship between anthropomorphism and comfort with robots. As shown in Figure

5a, the quantitative cartography shows that as the face trended from highly mechanized to highly humanoid, observers' psychological comfort with the robot rose to the initial apex of the moderately mechanized face (red dotted line). Past this point, psychological comfort with robots started to go down with increasing humanoids, reaching a low point (green dotted line) that represents a somewhat human-like robot face. However, it is noted that this low point is not the nadir of the cartography. Then, the anthropomorphism level positively correlates with psychological comfort until a fully human-like robot face (the 80th image). The curves of physiological comfort, holistic comfort, and trust progressed with a similar pattern to psychological comfort. Noteworthily, the trend of change in physiological comfort with robots is relatively flat. We can conclude that our cartographies regarding anthropomorphism and comfort with robots/trust illustrate some UV features endorsed by Mori (1970). Nevertheless, the point that represents the "*UV bottom*" is not necessary to be the nadir well below neutral.

5.2.2 Structural model

Two models, including formative comfort with robots and holistic comfort with robots, respectively, were tested to validate the hypotheses. The model testing results are demonstrated in Table 5. First, comfort with robots contributes to increased trust in robots ($\beta_{Model\ 1} = 0.402$, $p < 0.001$; $\beta_{Model\ 2} = 0.391$, $p < 0.001$), which further leads to higher intention to use robots ($\beta_{Model\ 1} = 0.387$, $p < 0.001$; $\beta_{Model\ 2} = 0.302$, $p < 0.001$). Therefore, H3 and H5 are supported. In addition, comfort with robots significantly contributes to usage intention ($\beta_{Model\ 1} = 0.337$, $p < 0.001$; $\beta_{Model\ 2} = 0.486$, $p < 0.001$), confirmed H4. Both Model 1 and Model 2 have sufficient explanatory power for the variance in comfort with robots, trust, and usage intention, respectively (Falk and Miller, 1992).

	Formative comfort (Model 1)	**Holistic comfort (Model 2)**
Comfort with robots → Trust	0.402^{***}	0.391^{***}
Trust → Usage intention	0.387^{***}	0.302^{***}
Comfort with robots → Usage intention	0.337^{***}	0.486^{***}
Control effect		
Emotional status→ Comfort with robots	$0.004^{n.s.}$	$0.002^{n.s.}$
Emotional status → Trust	0.035^{**}	0.036^{**}
Emotional status → Usage intention	-0.062^{***}	-0.059^{***}
Familiarity → Comfort with robots	0.082^{***}	0.031^{*}
Familiarity → Trust	0.031^{**}	0.052^{***}
Familiarity → Usage intention	$0.010^{n.s.}$	0.029^{*}
Previous experience with AI systems→ Comfort with robots	$-0.003^{n.s.}$	0.035^{***}
Previous experience with AI systems → Trust	$-0.006^{n.s.}$	-0.021^{*}
Previous experience with AI systems→ Usage intention	$0.005^{n.s.}$	$-0.014^{n.s.}$
Likeability → Comfort with robots	0.815^{***}	0.797^{***}
Likeability → Trust	0.422^{***}	0.439^{***}
Likeability → Usage intention	0.089^{**}	$0.040^{n.s.}$

Note: (1) * means $p < 0.05$, ** means $p < 0.01$, *** *means* $p < 0.001$; (2) Model 1: $R^2_{comfort\ with\ robots} = 73.3\%$, $R^2_{trust} = 69.2\%$, $R^2_{usage\ intention} = 53.7\%$; Model 2: $R^2_{comfort\ with\ robots} = 65.3\%$, $R^2_{trust} = 70.2\%$, $R^2_{usage\ intention} = 58.0\%$.

Table 5. Hypothesis testing results.

5.2.3 Post-hoc test: the mediating effect of trust

The mediation of trust was assessed by the mediation-analysis approach prescribed by Nitzl et al. (2016). We first examined the specific indirect path between comfort with robots and usage intention through trust and its significance. Once confirming the significance of the specific indirect path, we further tested the direct relationship between comfort with robots and usage intention. As reported in Table 6, the particular indirect relationship, i.e., comfort with robots → trust → usage intention, is significant, and the relationship between comfort with robots and usage intention is also substantial. Hence we can conclude a partial mediation through trust between comfort with robots and usage intention.

IV	**IV → Usage intention**	**IV → Trust**	**IV → Trust→ Usage intention**	**Mediation**
Formative comfort	0.376^{***}	0.672^{***}	0.284^{***}	Partial
Holistic comfort	0.501^{***}	0.633^{***}	0.199^{***}	Partial

Table 6. Mediation analysis results.

6 Discussion and conclusion

Motivated by a paucity of knowledge on user pre-interaction reactions to service robots, this study validated that a sufficient level of perceived comfort with a robot plays a significant role in users' willingness to engage in *r*-services. In particular, this study investigated consumers' pre-interaction response to service robots by delineating the influence of the anthropomorphism degree presented by robots on observers' comfort with robots and trust, and the mediating effect of trust between comfort with robots and usage intention based on the UVH and comfort theory. We found a curvilinear relationship between anthropomorphism and comfort with robots. Although it demonstrates some features central to the UV conceptualization by Mori (1970), it does not perfectly match the depiction of UV. The situation is similar when it comes to the relationship between anthropomorphism and trust. Furthermore, this study concludes a mediating role of trust between comfort with robots and usage intention with empirical evidence.

6.1 Implications for research and practice

By answering the research questions, this study makes several theoretical contributions. First, this study scrutinizes the pre-interaction reaction of users to service robots by investigating the influence of anthropomorphism degree on observers' comfort with robots and trust in robots. The current literature on customer responses to service robots has primarily focused on personal reactions in terms of technology-orientated views, such as the affordances of robots (Abrishami et al., 2014) and utilitarian functionality (Odekerken-Schröder *et al.*, 2022), service-orientated view, such as performance quality (Yoo et al., 2016) and service assessment (Yoganathan et al., 2021), and HRI views, such as perceived enjoyment (Wu *et al.*, 2014) and perceived sociability (Shin and Choo, 2011). Little attention has been paid to the pre-interaction responses to service robots to figure out how the physical presence of robots affects end-users' implicit social decision-making. Following the criteria prescribed by Mathur and Reichling (2016), we created a robot image sample pool and extracted a fine-grained spectrum in terms of anthropomorphism with progression from mechanical likeness to human likeness. Moreover, not only was the rank of anthropomorphism degree formed by an assessment penal but also self-reported by the participants. As such, we can minimize, to a large extent, the selection bias of robot images. The results reveal a curvilinear relationship between anthropomorphism and comfort with robots, as well as between anthropomorphism and trust, which features some UV resemblances. To this end, this study is among the first to cartographically investigate the UV-resemblance effect of robot anthropomorphism degree on the perceived comfort of robots and trust, laying a valuable background for future research to theorize customer responses to service robots or *r*-services. This study enriches the existing literature by illuminating the pre-interaction view regarding comfort with robots for setting a basis to comprehend consumer response to service robots from an ambidexterity view from pre-interaction to post-interaction in robotic research.

Furthermore, our study is among pioneering attempts to systematically introduce comfort theory into the study of customer responses to service robots. Even though previous studies have peripherally touched on the significance of users' comfort with robots (Duffy, 2003; Fong *et al.*, 1974; Groom and Nass, 2007), and a few studies have conceptualized its association with trust (Hancock, Billings, Oleson, *et al.*, 2011; Sanders *et al.*, 2011). The role of comfort with robots, induced by robot anthropomorphism, in penetrating end-user implicit social decision-making before adoption to use has been omitted in past studies. By addressing the role of comfort with robots in pre-interaction response, comfort theory offers a valuable theoretical lens to unmask the underlying mechanism of how consumers respond to service robots before actual interaction with robots. Notably, by drawing upon comfort theory, this study also developed and verified two measurements for comfort with robots, i.e., holistic comfort and formative comfort consisting of psychological comfort and physiological comfort. The proposed measure instruments can be used to determine the perceived valence and magnitude of comfort with robots in future empirical studies and facilitate future studies of *r*-service relationships.

Next, the present study advances theoretical development in understanding implicit social decision-making in the pre-interaction stage from the views of human-robot trust and comfort with robots. It enriches contemporary knowledge by understanding the underlying mechanism that highlights the role of trust in mediating the influence of comfort with robots on usage intention. This offers a deeper understanding of the trust mechanism in triggering usage intention in *r*-services together with comfort with robots and clarifies the connection between comfort with robots, usage intention, and trust.

Our findings also offer several valuable implications in practice. First, given the curvilinear relationship between anthropomorphism degree and comfort with robots/trust, our study endeavors to offer suggestions for robotic design and optimization that avoid falling into the "UV". Rather than overemphasizing anthropomorphism, robotic designers are recommended to ponder creating a safe range of comfort by deliberately focusing on non-human design locked on the stage before the first peak, which leads to a moderate extent of anthropomorphism and considerable comfort with robots and trust. This is because observers' discomfort reactions (UV bottom) are lurking in the progression of increasing anthropomorphism to reach the second peak. Alternatively, the assimilation of other presence attributes in robot design, such as cuteness design, may help to provoke observers' comfort feelings.

Second, considering that comfort with robots lays a basis for understanding end-users' pre-interaction response to service robots, *r*-service operators need to be aware of the importance of consumers' comfort level with the deployed robots since consumers' perceived comfort with a robot directly affects their acceptance of *r*-service, thereby the success of the robot deployment. With such an understanding in mind, *r*-service operators can come up with more valuable strategies that help with customer experience improvement.

Third, although previous studies indicated the significance of comfort with robots in developing trust (Evers *et al.*, 2008; Hancock, Billings, Oleson, *et al.*, 2011; Sanders *et al.*, 2011) and the success of HRI (Groom and Nass, 2007), the significant mediating role of trust between comfort with robots and usage intention should not be ignored. If the physical presence of a robot fails to provoke observers' initial trust, their usage intention is prone to decline. Bearing this in mind, *r*-service providers are encouraged to issue more strategies that raise and protect the trustworthiness of service robots, particularly from a social-psychological perspective in the pre-interaction stage.

6.2 Limitations and future research

Several limitations of this study present opportunities for future research. First, several predictors of comfort with robots may exist from robot attributes in terms of physical presence, such as social presence, cuteness, and aesthetic value. This study merely delineates the influence of robot anthropomorphism on comfort with robots. Therefore, it is promising to investigate more antecedents that provoke comfort with robots in end-users in future studies, as well as other pre-interaction perceptions. Second, even though this study leverages a sample pool comprising 80 real-world robot images to obtain fine-grained statistical analysis results on the influence of anthropomorphism, the possibility of biased results due to the selection of robot face images cannot be ruled out. Future research to address this concern is encouraged. Third, whereas this study is based on observing robot face images, more interesting findings may be achieved by using robot entities as stimuli in experiments or actual service settings and taking the effect of robot movement into account, which allows more worthwhile research and managerial insights to burgeon in the robotic research of IS discipline.

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