7-8-2023

Examining Applicability of Uncanny Valley Hypothesis: A Large-Scale Study

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Completed Research Paper

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Abstract

Despite a growing interest in applying the uncanny valley hypothesis (UVH) in IS studies, there is a paucity of knowledge on the applicability of UVH and its strength. By summarizing a set of attitudinal variables popularized in the extant IS literature on AI robots, this study examined the strength and applicability of UVH on a large, objectively chosen sample of 80 real-world robots face against these variables. We demonstrate that while robot anthropomorphism does affect users' attitudes toward the robot, its effects do not necessarily follow a UV pattern, and it has a very limited explanatory power toward users' attitudinal responses. In addition, robot anthropomorphism has a much stronger linear-like association with a perceived social presence than with the commonly used response variable of perceived likability. Our results offer insights into understanding the applicability and strength of the uncanny valley effect and the impacts of robot anthropomorphism on users' perceptions.

Keywords: Uncanny Valley Theory, Uncanny Valley Hypothesis, AI robot, Anthropomorphism, Threat, Adoption

Introduction

Along with recent advances in artificial intelligence (AI) and its applications in the service domain, both business and scientific communities exhibit a strong and growing interest in using tangible AI robots (hereafter referred to as AI robots) to offer human-like services in the real world. Nonetheless, designing an IS artifact with physical existence, like AI robots, exhibits an unprecedented challenge for IS communities. Extant IS research and theories that have been dominantly built upon studying digital IS that are intangible in nature may not be applicable in the domain of tangible IS (see e.g., Schuetz and Venkatesh 2020). In this vein, the uncanny valley hypothesis (UVH), originating from human-computer interaction (HCI) research (Mori 1970; Mori et al. 2012), has thus been widely utilized in IS research on AI robots.

The UVH postulates that robot anthropomorphism, also termed robot human-likeness, shapes users' attitudinal responses to the robots, such as perceived likability, in a nonlinear manner (Mori 1970; Mori et al. 2012). Such a nonlinear relationship is often referred to as the uncanny valley effect. Currently, UVH is among the most applied theoretical lens in IS literature on AI robots. Nonetheless, as highlighted by the review of Li and Suh (2021), inconsistent results regarding the impact of anthropomorphism are prevalent in the literature.

Despite the prevalence of UVH in IS studies, there is a paucity of knowledge on the strength of the hypothesis and its scope of applicability. While the UVH has maintained substantial research interest from the scientific community in the past decades (Wang et al. 2015), "empirical evidence for the uncanny valley hypothesis is still ambiguous if not non-existent" (Kätsyri et al. 2015 p. 2). Most studies attempting to validate the hypothesis have compared a few human and robot faces with varying degrees of opacity (Mathur and Reichling 2016). Such analysis of a few robot designs makes it difficult to estimate the predictive power and applicability of the UVH, which may demand analyzing a large sample of robot designs (Mathur and Reichling 2016).

While robot anthropomorphism exhibits an important attribute of robots' physical appearance, understanding its applicability and predictive power on users' attitudinal responses is of great importance. Many IS studies assume robot anthropomorphism is a precursor of key perceptual variables (including trust, social presence, perceived risk, privacy invasion, likability, threat, and usage intention) (see, e.g., Moussawi and Koufaris 2019; Qiu and Benbasat 2009), but little empirical evidence is available in support of the existence of hypothesized UV effect and to justify the strength of the effect. For instance, while past studies assume a robot with high anthropomorphism would have a higher level of perceived threat and likeability by comparing a couple of robot designs, how valid such an assumption is? In addition, is it possible to design a robot with a high anthropomorphism but a low perceived threat?

This exploratory study attempts to address the challenges discussed above by studying a large sample of real-world robot faces used in earlier research and an associated collection of 3,893 user responses. This method is motivated by and based on the technique introduced by Mathur and Reichling (2016), who explored the impact of robot anthropomorphism on both perceived likability and trust. In this study, we investigate a similar collection of 80 real-world robot faces based on the work of Mathur and Reichling (2016) but employ two different measures of anthropomorphism. Furthermore, in addition to likability and trust, we identify a list of attitudinal variables commonly used in IS research by reviewing extant literature and empirically examining the strength of the UV effects on these variables.

The rest of the paper is structured as follows. In the next section, we introduce the UVH and review the extant IS studies on AI robots, then describe our research methodology. We then explain the results in section 4 and discuss the study's implications in section 5. We conclude the paper in section 6.

Earlier Studies and Research Framework

The UVH and UV effect

The UVH assumes that people's attitudinal responses to robot anthropomorphism, such as perceived familiarity or perceived likability, follow a nonlinear pattern, as shown in Figure 1 (Mori 1970; Mori et al. 2012). When people encounter a highly machine-like robot, they will dedicate their attention to the human-like part of the robot. Because people tend to like other humans, observing human-like parts of the robots will elicit a feeling of familiarity and, thus, positive emotional responses. As a result, people will develop more positive emotional and attitudinal reactions towards robots if the robots become more human-like in appearance and motion (c.f. Akdim et al. 2021; Lee et al. 2011; Li and Sung 2021). This trend continues until it reaches a certain point beyond which people find the nonhuman imperfections of robots unsettling. This dip in appraisal indicates the effect of the uncanny valley (Ho and MacDorman 2010). Nonetheless, people's attitudinal reactions will turn positive again and reach a high level once the robots become indistinguishable from humans. In accordance with the UVH, people would yield even stronger emotional responses when the robots are moving instead of remaining still.

Noticeably, the UVH was originally put forward as a speculation that was not tested with any empirical data (Geller 2008). Thus far, the hypothesis has generated much discussion among robotics researchers (Kätsyri et al. 2015; Wang et al. 2015). While some scholars accept Mori's assumption as a theory, others reject it as being "pseudoscientific" (see e.g. Brenton et al. 2005). Empirical evidence has been accumulated from past studies examining UV effects, yielding ambiguous support for the hypothesis. Several reviews on UVH are available (see e.g. Kätsyri et al. 2015; Wang et al. 2015). Apart from supporting evidence, these reviews also highlight a list of past studies that reject or fail to detect the UV effect (Kätsyri et al. 2015; Wang et al. 2015).

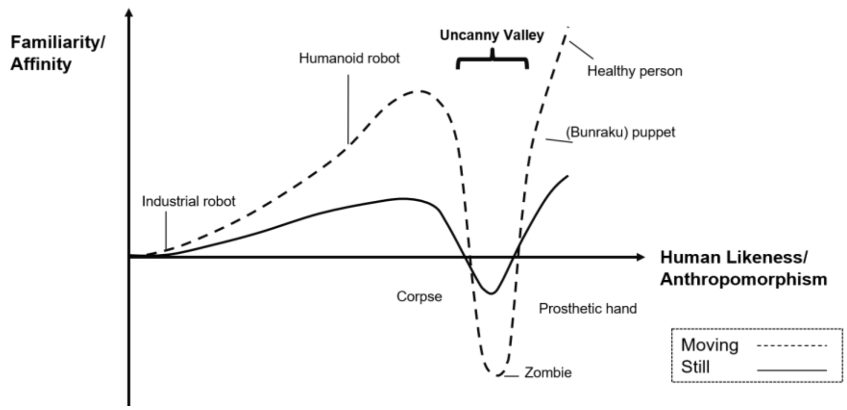

Figure 1. Uncanny Valley Hypothesis (Mori 1970; Mori et al. 2012)

Past studies have attempted to validate the UVH through different research designs. Nonetheless, "most studies attempting to address the issue have employed progressively morphed blends of human and robot faces, in which two face images are digitally overlaid with varying degrees of opacity" (Mathur and Reichling 2016, p. 22). Studying a small sample of robot designs may not support capturing the effect of robot anthropomorphism in its full spectrum range. In this regard, Mathur and Reichling (2016) attempted to validate the theory using a large sample of 80 real-world robot faces, which has been regarded as support for the existence of UV effects (e.g., Wang et al. 2015). Nonetheless, their study only detects a weak UV effect by highlighting a limited predictive power of perceived robot anthropomorphism (or a small R2 of 0.29 for perceived likability (or affinity) and only 0.07 for perceived trust), suggesting a need to further examine the applicability and strength of the hypothesis.

Earlier studies on AI robots

Motivated by the UVH, robot anthropomorphism is among the most often investigated factors of IS studies on AI robots, as shown in Table A in the Appendix, which summarizes the key perceptual variables that have been empirically studied in association with robot anthropomorphism but have not necessarily served as a resultant or predicting variable of anthropomorphism. For instance, social presence has been theorized as a precursor of the anthropomorphism (Schuetzler et al. 2020) or as its product (Qiu and Benbasat 2009). By a systematic search of recent studies on AI robots, our review reveals that factors such as trust, social presence, perceived risk, privacy invasion, likability, and usage intention, are among the most discussed and studied factors associated with robot anthropomorphism. Other factors derived from interacting with a robot, such as the perceived intelligence of the robot or the usefulness of robotic services, are not considered in our study.

In addition to the above-listed factors, our study considers perceived realistic threats and identity threats. This is motivated by a paradox we observed in the literature mainly outside the IS domain. The association between perceived realistic threats and perceived identity threats, and robot anthropomorphism has been widely discussed in the HCI literature (see Rzepka and Berger 2018), suggesting that high anthropomorphism and high autonomy of robots lead to strong perceived identity and realistic threats and negative attitude toward the robot (Huang et al. 2021; Yogeeswaran et al. 2016; Złotowski et al. 2017). By studying standardized pictures of 40 robots, Rosenthal-Von Der Pütten and Krämer (2014) concluded that enhanced anthropomorphism increases both perceived likeability and perceived threat, which cannot be well explained by the UVH. Thus, we believe incorporating threat into the analysis would offer a more complete understanding on the UVH effects.

In the extant literature, perceived anthropomorphism is often assumed to have a linear impact on users' perceptions, including trust, perceived enjoyment in interacting with robots, and adoption intention, but the findings have often been contradictory (or a review see Li and Suh 2021). While a few studies have demonstrated a positive impact of anthropomorphism on users' willingness to use AI-enabled technology, studies demonstrating a negative impact can also be found (Li and Suh 2021). We also observed a paradox in extant research regarding the impact of highly anthropomorphic robots on user attitudes (Akdim et al. 2021; Huang et al. 2021). For instance, while UVH assumes a positive impact of high anthropomorphism on users' reception of robots, Akdim et al. (2021) show three different studies that customers reject very human-like robots in service encounters. Another example is the relationship between trust and anthropomorphism, with a positive (Waytz et al. 2014), negative (Schroeder and Schroeder 2018), and no significant (Moussawi et al. 2021) influence of anthropomorphism on trust reported in their studies.

Hypotheses Building

IS studies on service robots are still at an early stage, and most studies (see Table A in the Appendix) typically offer a supporting view of the UVH. Building on these past IS studies and other studies in support of UVH, we assume the existence of UVH on users' attitudinal and emotional responses. Thus, we postulate a UV-shape relationship between robot anthropomorphism and likeability (Mathur et al. 2020; Mathur and Reichling 2016; Mende et al. 2019), trust (Mathur and Reichling 2016; Zhang et al. 2021), social presence (Blut et al. 2021; Dubosc et al. 2021), privacy invasion (Benlian et al. 2020; Xie and Lei 2022), and use intention (Blut et al. 2021; Kim et al. 2023; Xie and Lei 2022). Specifically, the UV-shaped relationship indicated that the relationship between the two variables would follow the pattern described by the UV hypothesis (see Figure 1). In other words, we argued that when a robot exhibits a relatively high anthropomorphism that is uncomfortable or unsettling, similar to a zombie-like robot, individuals tend to perceive low levels of likeability, trust, social presence, and user intention while expressing greater privacy concerns regarding the robot. Accordingly, we submit that:

H1. Robot anthropomorphism has a UV-shaped relationship with perceived likeability.

H2. Robot anthropomorphism has a UV-shaped relationship with perceived trust.

H3. Robot anthropomorphism has a UV-shaped relationship with perceived social presence.

H4. Robot anthropomorphism has a UV-shaped relationship with perceived privacy invasion.

H5. Robot anthropomorphism has a UV-shaped relationship with use intention.

Past studies on the impact of anthropomorphism on the perceived risk (Kim and McGill 2011; Yoganathan et al. 2021), perceived identity threat (Yogeeswaran et al. 2016), realistic threat (Yang et al. 2021; Yogeeswaran et al. 2016) are normally conducted by comparing two robots with high vs. low anthropomorphism design, without considering the robots that yield an unsettling feeling. In other words, robot anthropomorphism has been treated as a binary variable of high vs. low anthropomorphism scores, other than being computed as a continuous variable. Accordingly, UV effect of robot design or anthropomorphic robots that may yield possible unsettling feeling was not considered. This study tests hypotheses by measuring anthropomorphism as a wide spectrum of scores. In this vein, in line with UVH, we argue that the UVH should also be applicable on users' perceived risk, realistic and identify threats. Accordingly, we submit that:

H6. Robot anthropomorphism has a UV-shaped relationship with perceived risk.

H7. Robot anthropomorphism has a UV-shaped relationship with perceived identity threat.

H8. Robot anthropomorphism has a UV-shaped relationship with perceived realistic threat.

Research Methodology

In line with the work of Mathur and Reichling (2016), we utilize a similar large sample of 80 real-world robot faces to examine users' reception of the robots, as shown in Figure 2. Most of the robot faces (n = 73) used are derived from the work of Mathur and Reichling (2016) by using online image search functions to obtain the same images of the same robots. The images of seven robots not available online were replaced by seven new, closely similar images. Mathur and Reichling (2016) used a set of strict criteria, including eight inclusion criteria and four exclusion criteria, in their robot face selection to reduce the bias caused by the manner of presentation, expressions, poses, background settings, viewing angles, and so on. We applied the same criteria in selecting the new robot face images.

Figure 2. The pool of robot face stimuli numbered and displayed in ascending order of anthropomorphism score

A survey questionnaire was developed to capture users' perceptions of the robots. Because the measure of anthropomorphism has been deemed to affect the research results (Li and Suh 2021; Lu et al. 2019), we use two different measures of anthropomorphism in the analysis, namely a between-subject measure and a within-subject measure, which we believe will offer more comprehensive results. The **within**-subject measure is built upon the work of Mathur and Reichling (2016) and Mathur et al. (2020), which ranks robot images on anthropomorphism by requesting experiment participants to view and compare all 80 robot images. We utilized these same rankings as the basis of the within-subject measure of robot anthropomorphism. As noted above, images of seven new robot faces were added to the pool of samples. A panel of 4 participants was organized to assess the ranks of the new robot faces in a two-step method. Specifically, the panel first gave a rank of these new images individually and then jointly discussed the rank differences to achieve a consensus. As a result, the **within**-subject measure of robot anthropomorphism is determined.

The **between**-subject measure of anthropomorphism refers to mechano-humanness scores of robots by obtaining participants' evaluations of the robot faces from "very machine-like (-100) to very human-like (100)". The between-subject measure of anthropomorphism represents a more commonly used measure of robot anthropomorphism, deriving from users' subjective perception of anthropomorphism on individual robot faces. Measures for trust, social presence, perceived risk, privacy invasion, likability, threat, and usage intention were obtained from previous works, as shown in Table 1. We performed a pilot study with 60 participants. Based on their responses, we enhance the reliability and validity of the measurements of the constructs.

Constructs	Number of items	Sources
1. Trust	5	Etemad-Sajadi (2016), Nunamaker et al. (2011), Ahmad (2009), Gefen (2002)
2. Social presence	6	Etemad-Sajadi (2016), Qiu and Benbasat (2009), Gefen and Straub (2004)
3. Perceived risk	5	Chi et al.(2021)
4. Familiarity	4	Chi et al.(2021)
5. Privacy invasion	6	Benlian et al. (2020), Ayyagari et al. (2011)
6. Likeability	6	Seymour et al. (2021), Nunamaker et al. (2011)
7. Realistic threat	7	Mende et al. (2019), Złotowski et al. (2017), *self-developed*
8. Identity threat	8	Keijsers et al. (2021), Mende et al. (2019), Złotowski et al. (2017)
9. Usage intention	3	Qiu and Benbasat (2009)

Table 1. Measures

Amazon Mechanical Turk (AMT) was used to sample subjects. AMT is a crowdsourcing platform where workers perform online tasks in exchange for payment. So-called "master workers" of AMT, who have demonstrated a high degree of success in performing past tasks, were recruited for the experiments. Given the length of the survey instrument, each experiment participant was invited to evaluate only one robot image, rather than all 80 images. Our aim was to collect approximately 50 responses for each robot face. Six attention-check questions were included in the survey, and responses of those who failed to respond correctly to them were automatically excluded. The respondents were first asked about their previous experience using AI-based systems. Those without any AI-based system were not qualified to participate in the survey and thus dropped from the study. As a result, 3,893 responses were collected, i.e., on average, 48.7 responses for each image. The survey included several questions about participants' demography. According to the data, most survey respondents are males (N = 2359, 60.6%), and between 26 and 45 years old (N = 2911, 74.8%), as shown in table 2. Reliability and validity measures pertinent to latent variables were estimated, which are presented in table 3.

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.

Constructs	Cronbach's Alpha	CR	AVE	Minimal factor-loading	1	2	3	4	5	6	7	8	9
1. Trust	0.959	0.968	0.859	0.907	**0.927**								
2. Social presence	0.958	0.966	0.802	0.829	0.755	**0.895**							
3. Perceived risk	0.964	0.972	0.873	0.899	-0.212	0.024	**0.934**						
4. Familiarity	0.909	0.936	0.788	0.723	0.385	0.453	0.159	**0.888**					
5. Privacy invasion	0.961	0.964	0.818	0.760	-0.151	0.017	0.742	0.078	**0.905**				
6. Likeability	0.946	0.957	0.790	0.813	0.803	0.817	-0.070	0.419	-0.045	**0.889**			
7. Realistic threat	0.960	0.965	0.774	0.825	0.143	0.274	0.639	0.265	0.531	0.213	**0.880**		
8. Identity threat	0.974	0.978	0.847	0.886	0.266	0.410	0.602	0.428	0.452	0.334	0.855	**0.920**	
9. Usage intention	0.974	0.983	0.950	0.969	0.707	0.586	-0.126	0.366	-0.056	0.666	0.110	0.258	**0.975**
Note: The numbers in bold type on the diagonal line represent the square root of the corresponding variable average variance extracted.													

Table 3. Reliability and validity of latent variables

Results

Measures of anthropomorphism

The scores of the between-subject measure of anthropomorphism may not be fully in line with that of the within-subject measure. Evidently, within-subject measure of anthropomorphism of a robot is established with by comparing the robot with other robots to achieve a relatively anthropomorphism score, while between-subjective measure of anthropomorphism fully derives from one's perceptions of an individual robot without offering any other robots for comparison. To validate the UV effects, both measures of anthropomorphism were tested. The between-subject and within-subject measures have a correlation coefficient of 0.927 ($p < 0.000$), indicating that the two measures have high consistency, albeit with some notable differences. For instance, as shown in Figure 3, a robot with a high rank in within-in subject measure may have a relatively low score in between-in subject measure of anthropomorphism.

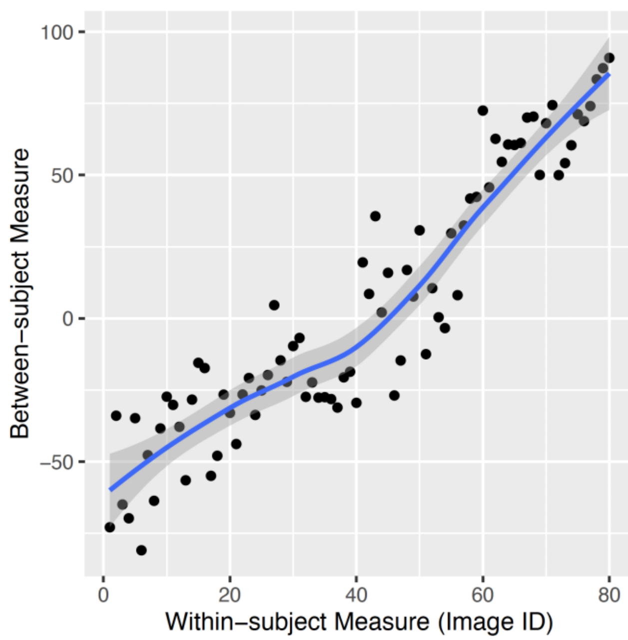

Figure 3. Correlation between the between-subject measure and the within-subject measure of anthropomorphism (R2 = 85.9%)

Examining the Applicability and Strength of UVH

We first examined the hypothesized UV effects based on using two different measures of robot anthropomorphism on robot likability and trust, respectively. We modeled the relationship between average between-subject anthropomorphism and likability scores per image via polynomial regression, and the approach is inspired by the work of Mathur and Reichling (2016). Because we are interested in the possible polynomial curves (e.g., UV curve) that can best explain the variance in the variables of interest, adjusted R2 was used as criteria to choose the best-fitting model by comparing polynomial terms (PTs) of anthropomorphism score from first-degree to fourth-degree.

The results indicated that third-degree models offer the highest adjusted R2 when modeling the relationship between anthropomorphism and likability (see Appendix Figures A1 and A2). The variances explained by between-subject and within-subject anthropomorphism are 0.36 and 0.31, respectively, which is slightly higher than the value (R2 = 0.29) reported by the work of Mathur and Reichling (2016). This may be caused by our use of multiple items for measuring likability in the current study, unlike the work of Mathur and Reichling (2016), which used a one-item measurement of likability. This result supports H1, that is, the nonlinear UV effect for the relationship between anthropomorphism and likability. However, it also indicates that anthropomorphism has limited explanatory power over perceived robot likability since more than 60% of the variance of perceived likability cannot be explained by robot anthropomorphism.

We modeled the relationship between robot anthropomorphism and perceived trust using a similar method reported above. Nonetheless, the best fitting models for trust are first-degree (or linear) and third-degree polynomial models for between-subject (R2 = 0.19) and within-subject (R2 = 0.20) measures of robot anthropomorphism, respectively (see Figures A3 and A4), thereby partially supporting H2. In line with the work of Mathur and Reichling (2016), this result also highlights a limited explanatory power of perceived robot anthropomorphism on trust, and most variance (80%) of the perceived trust of robot faces cannot be explained by robot anthropomorphism. As shown in figures A1-A4, some robot faces exhibit very high or low likability and trust scores always from the predicted values by anthropomorphism. This indicates that the scores of perceived likeability and trust of these robots may better be explained by other robot-appearance attributes other than anthropomorphism. This also implies a need to explore other robot appearance attributes in addition to anthropomorphism in future studies.

We also examined the predictive power of robot anthropomorphism on other attitudinal and perceptual variables widely used in IS robot studies and inspected whether there is a nonlinear UV effect with these variables. Between-subject anthropomorphism was found to explain 11.5% (perceived risk), 73.9% (social presence), 15.2% (privacy invasion), 3.1% (realistic threat), 5.5% (identity threat), and 5.9% (usage intention) of the variances, while within-subject anthropomorphism was found to explain 9.3%, 56.3%, 20%, 0.7%, 0.3% and 6.3% of variances of the same variables, as shown in Figure 4 and table 4. The impact of anthropomorphism on perceived risk, social presence and privacy invasion do not follow a UV curve for between-subject measure of robot anthropomorphism, therefore partially supporting H3, H4 and H6, as shown in Figures A5 to A10 in Appendix.

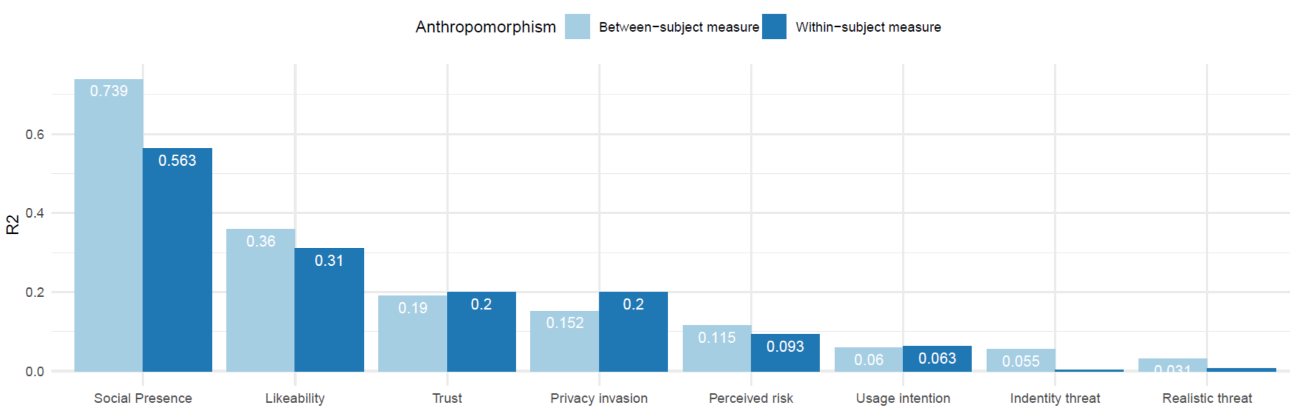

Figure 4. R-square explained by robot anthropomorphism

	Between-subject anthropomorphism	Within-subject anthropomorphism	Support
Likability (H1)	36% (third-degree PT)	31% (third-degree PT)	Yes
Trust (H2)	19% (First-degree PT)	20% (third-degree PT)	Partially
Social presence (H3)	73.9% (third-degree PT)	56.3% (third-degree PT)	Partially
Privacy invasion (H4)	15.2% (fourth-degree PT)	20% (fourth-degree PT)	Partially
Usage intention (H5)	6.0% (first-degree PT)	6.3% (third-degree PT)	No
Perceived risk (H6)	11.5% (Second-degree PT)	9.3% (third-degree PT)	Partially
Realistic threat (H7)	3.1% (fourth-degree PT)	0.7% (second-degree PT)	No
Identity threat (H8)	5.5% (fourth-degree PT)	0.3% (second-degree PT)	No

Table 4. Explanatory Power of Robot Anthropomorphism on Different perceptual and attitudinal Variables (Note: The degrees of the polynomial term (PT) for the best-fitting models are included in the bracket)

As shown in Figures A11 to A16 in Appendix, the relationships between robot anthropomorphism and identity threats and realistic threats and usage intention do not exhibit an apparent nonlinear curve of the UV effect, therefore rejecting both H5, H7 and H8. Furthermore, even though past studies have implied that users develop different perceptions related to issues such as privacy, risks, and threats, by observing a robot, our result shows that the anthropomorphism of robots can only explain a very small percentage of such perceptions.

Discussion and Implications

Our study makes several contributions to IS research on AI robots. First, the study provides a deeper understanding of robot anthropomorphism. Using two different measures of robot anthropomorphism, we found that perceived anthropomorphism is a complex notion, affected by whether other robot faces are offered as reference substances. As a result, between-subject and within-subject measures of robot anthropomorphism differ in their values but also their effects on perceptual factors, such as perceived trust and perceived identity threat. Our results offer empirical evidence to highlight a need for the research community to better understand perceived anthropomorphism and the factors that affect it.

Second, the results offer useful insights into the applicability and strength of the UVH. In line with the work of Mathur and Reichling (2016), we found a UV-shaped relationship between robot anthropomorphism and perceived likability by using two different anthropomorphism measures. Furthermore, we found a similar relationship between trust and the within-subject measure of anthropomorphism. Nonetheless, the relationship between trust and the between-subject measure of anthropomorphism is linear. In other words, there might exist factors that moderate the relationship between trust and between-subject measure of anthropomorphism, making the relationship between the two variables relatively more consistent. Nonetheless, such factors may have a very weak effect on perceived anthropomorphism when the anthropomorphism scores are determined with a direct comparison of different robot faces. We found a limited explanatory power of the robot anthropomorphism on both perceived likeability and trust, which is consistent with the work of Mathur and Reichling (2016). In addition, we observed even lower explanatory power of robot anthropomorphism on other perceptual and attitudinal variables, including risk, privacy invasion, realistic and identity threat, and usage intention. While extant IS studies have widely utilized robot anthropomorphism as a precursor of perceptual factors on AI robots, our study indicates that anthropomorphism may not necessarily be the best variable explaining these perceptions.

Third, the study offers useful insights into the debate on the contradicting findings on the impact of robot anthropomorphism on different variables (Li and Suh 2021). From Figure A1-A16 in Appendix it can be observed that many robot faces are located far away from the lines of predicted values. This indicates variances that robot anthropomorphism cannot explain. In addition, of the eight hypotheses put forward based on UV effect, only one is fully supported. This finding indicates a need for IS scholars to rethink the current theorization of the impact of robot anthropomorphism and a necessity to understand other robot appearance attributes to interpret robot-elicited perceptions.

The findings also imply a limit in the applicability of UVH in understanding users' perceptions of robots. On one hand, robot anthropomorphism has a limited explanatory power over users' perceptions. On the other hand, the relationships between robot anthropomorphism and the different perceptual variable do not follow a UV pattern. The study also reveals new insights on several extant assumption on the impact of robot anthropomorphism. For instance, high anthropomorphic robots do not necessarily trigger the strongest perceptions of identity threats, realistic threats and usage intention. In addition, given a large variance observed in Figure A1-A16 in Appendix, we can identify counter-intuitive robot face designs. For instance, we can observe a robot face with low anthropomorphic score, but high scores in both trust and intention to use, as well as low score in risk.

Finally, we found that robot anthropomorphism strongly correlates with perceived social presence with a very high explanatory power (73.9%) by using a between-subject measure. It is worth noting that the relationship between the two variables is close to linear, albeit by using two different anthropomorphism measures. This may indicate that perceived social presence can be a more relevant resultant variable of robot anthropomorphism than perceived likeability that is now commonly used as the key resultant variable of robot anthropomorphism.

Limitations and Future Research

The study has a few limitations. First, while our results are based on studying the 80 different designs of robots, our selection – as any selection - of robot face images could bias the results. Second, although two different measures of robot anthropomorphism were used, a more precise measure may exist. Third, our study did not explain the difference between the within-subject and between-subject measures of robot anthropomorphism. Fourth, the study did not investigate the factors affecting anthropomorphism. For instance, past studies show that gender affects users' perception and response to robots (Crowell et al. 2009; e.g., Siegel et al. 2009). However, the gender difference was not considered in the study. on users' reception of robots.

Nevertheless, the results of the current study create a basis for us to conduct future research. Specifically, measuring different attributes pertinent to each robot image enables us to identify the robot designs eliciting the strongest as well as the weakest feelings of, for instance, trust, risk, and privacy invasion. Through studying systematically different robot images, we may extract other possible robot appearance attributes to understand the causes of different perceptions of robots and interaction with them.

Acknowledgements

The authors gratefully acknowledge that project is partly supported by the Finnish National Agency for Education (Project ID: AIRobinSerS), the Jenny and Antti Wihuri Foundation (Project ID: Embracing the Future: Service Robots for Business Values and Social Welfare), and the Academy of Finland (Funding for mobility cooperation).

References

Ahmad, A. R. 2009. "The Product Effect: A New Technique for Automotive Market Research," in *Cumulus 38° South Conference: Hemispheric Shifts Across Learning, Teaching and Research*, Melbourne, Australia.

Akdim, K., Belanche, D., and Flavián, M. 2021. "Attitudes toward Service Robots: Analyses of Explicit and Implicit Attitudes Based on Anthropomorphism and Construal Level Theory," *International Journal of Contemporary Hospitality Management* (ahead-of-p).

Ayyagari, R., Grover, V., and Purvis, R. 2011. "Technostress: Technological Antecedents and Implications," *MIS Quarterly* (35:4), pp. 831–858.

Benlian, A., Klumpe, J., and Hinz, O. 2020. "Mitigating the Intrusive Effects of Smart Home Assistants by Using Anthropomorphic Design Features: A Multimethod Investigation," *Information Systems Journal* (30:6), John Wiley & Sons, Ltd, pp. 1010–1042.

Blut, M., Wang, C., Wünderlich, N. V, and Brock, C. 2021. "Understanding Anthropomorphism in Service Provision: A Meta-Analysis of Physical Robots, Chatbots, and Other AI," *Journal of the Academy of Marketing Science* (49), pp. 632–658.

Blut, M., Wünderlich, N. V., and Brock, C. 2018. "Innovative Technologies in Branded-Service Encounters: How Robot Characteristics Affect Brand Trust and Experience," in *International Conference on*

Information Systems 2018, pp. 1–9.

Brendel, A. B., Greve, M., Diederich, S., Bührke, J., and Kolbe, L. M. 2020. "'You Are an Idiot!' - How Conversational Agent Communication Patterns Influence Frustration and Harassment," *26th Americas Conference on Information Systems, AMCIS 2020*, pp. 0–10.

Brenton, H., Gillies, M., Ballin, D., and Chatting, D. 2005. "The Uncanny Valley: Does It Exist," in *In Proceedings of Conference of Human Computer Interaction, Workshop on Human Animated Character Interactio*, Edinburgh, pp. 2–5.

Bruckes, M., Westmattelmann, D., Oldeweme, A., and Schewe, G. 2019. "Determinants and Barriers of Adopting Robo-Advisory Services," in *Proceeding of the Fortieth International Conference on Information Systems*.

Chi, O. H., Jia, S., Li, Y., and Gursoy, D. 2021. "Developing a Formative Scale to Measure Consumers' Trust toward Interaction with Artificially Intelligent (AI) Social Robots in Service Delivery," *Computers in Human Behavior* (118), p. 106700.

Crowell, C. R., Scheutz, M., Schermerhorn, P., and Villano, M. 2009. "Gendered Voice and Robot Entities: Perceptions and Reactions of Male and Female Subjects," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems,* pp. 3735–3741.

Danckwerts, S., Meißner, L., and Krampe, C. 2020. ""Hi, Can You Recommend a Movie?" Investigating Recommendation Chatbots in Media Streaming Services," in *ECIS 2020 Proceedings*.

Diederich, S., Janßen-Müller, M., Brendel, A. B., and Morana, S. 2020. "Emulating Empathetic Behavior in Online Service Encounters with Sentiment-Adaptive Responses: Insights from an Experiment with a Conversational Agent," *40th International Conference on Information Systems*.

Dubosc, C., Gorisse, G., Christmann, O., Fleury, S., Poinsot, K., and Richir, S. 2021. "Impact of Avatar Facial Anthropomorphism on Body Ownership, Attractiveness and Social Presence in Collaborative Tasks in Immersive Virtual Environments," *Computers and Graphics (Pergamon)* (101), pp. 82–92.

Etemad-Sajadi, R. 2016. "The Impact of Online Real-Time Interactivity on Patronage Intention: The Use of Avatars," *Computers in Human Behavior* (61), pp. 227–232.

Ge, R., Zheng, Z. (Eric), Tian, X., and Liao, L. 2021. "Human-Robot Interaction: When Investors Adjust the Usage of Robo-Advisors in Peer-to-Peer Lending," *Information Systems Research* (32:3), pp. 774–785.

Gefen, D. 2002. "Customer Loyalty in E-Commerce," *Journal of the Association for Information Systems* (3:1), pp. 27–53.

Gefen, D., and Straub, D. W. 2004. "Consumer Trust in B2C E-Commerce and the Importance of Social Presence: Experiments in e-Products and e-Services," *Omega* (32:6), pp. 407–424.

Geller, T. 2008. "Overcoming the Uncanny Valley," *IEEE Computer Graphics and Applications* (28:4), pp. 11–17.

Ho, C. C., and MacDorman, K. F. 2010. "Revisiting the Uncanny Valley Theory: Developing and Validating an Alternative to the Godspeed Indices," *Computers in Human Behavior* (26:6), Elsevier Ltd, pp. 1508–1518.

Huang, H. L., Cheng, L. K., Sun, P. C., and Chou, S. J. 2021. "The Effects of Perceived Identity Threat and Realistic Threat on the Negative Attitudes and Usage Intentions Toward Hotel Service Robots: The Moderating Effect of the Robot's Anthropomorphism," *International Journal of Social Robotics* (13:7), Springer Netherlands, pp. 1599–1611.

Kätsyri, J., Förger, K., Mäkäräinen, M., and Takala, T. 2015. "A Review of Empirical Evidence on Different Uncanny Valley Hypotheses: Support for Perceptual Mismatch as One Road to the Valley of Eeriness," *Frontiers in Psychology* (6), pp. 1–16.

Keijsers, M., Kazmi, H., Eyssel, F., and Bartneck, C. 2021. "Teaching Robots a Lesson: Determinants of Robot Punishment," *International Journal of Social Robotics* (13:1), pp. 41–54.

Kim, S., and McGill, A. L. 2011. "Gaming with Mr. Slot or Gaming the Slot Machine? Power, Anthropomorphism, and Risk Perception," *Journal of Consumer Research* (38:1), pp. 94–107.

Kim, T., Lee, O. K. D., and Kang, J. 2023. "Is It the Best for Barista Robots to Serve like Humans? A Multidimensional Anthropomorphism Perspective," *International Journal of Hospitality Management* (108), Elsevier Ltd.

Lee, N., Shin, H., and Shyam Sundar, S. 2011. "Utilitarian vs. Hedonic Robots: Role of Parasocial Tendency and Anthropomorphism in Shaping User Attitudes," in *HRI 2011 - Proceedings of the 6th ACM/IEEE International Conference on Human-Robot Interaction*, pp. 183–184.

Li, M., and Suh, A. 2021. "Machinelike or Humanlike? A Literature Review of Anthropomorphism in AI-Enabled Technology," in *Proceedings of the Annual Hawaii International Conference on System Sciences*, pp. 4053–4062.

Li, X., and Sung, Y. 2021. "Anthropomorphism Brings Us Closer: The Mediating Role of Psychological Distance in User–AI Assistant Interactions," *Computers in Human Behavior* (118:January), Elsevier Ltd, p. 106680.

Lu, L., Cai, R., and Gursoy, D. 2019. "Developing and Validating a Service Robot Integration Willingness Scale," *International Journal of Hospitality Management* (80:January), pp. 36–51.

Mathur, M. B., and Reichling, D. B. 2016. "Navigating a Social World with Robot Partners: A Quantitative Cartography of the Uncanny Valley," *Cognition* (146), pp. 22–32.

Mathur, M. B., Reichling, D. B., Lunardini, F., Geminiani, A., Antonietti, A., Ruijten, P. A. M., Levitan, C. A., Nave, G., Manfredi, D., Bessette-Symons, B., Szuts, A., and Aczel, B. 2020. "Uncanny but Not Confusing: Multisite Study of Perceptual Category Confusion in the Uncanny Valley," *Computers in Human Behavior* (103), pp. 21–30.

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., and Shanks, I. 2019. "Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses," *Journal of Marketing Research* (56:4), pp. 535–556.

Mori, M. 1970. "The Uncanny Valley," *Energy* (7), pp. 33–35.

Mori, M., AcDorman, K. F., and Kageki, N. 2012. "The Uncanny Valley," *IEEE Robotics and Automation Magazine* (19:2), IEEE, pp. 98–100.

Moussawi, S., and Koufaris, M. 2019. "Perceived Intelligence and Perceived Anthropomorphism of Personal Intelligent Agents: Scale Development and Validation," in *Proceedings of the 52nd Hawaii International Conference on System Sciences* (Vol. 6), pp. 115–124.

Moussawi, S., Koufaris, M., and Benbunan-Fich, R. 2021. "How Perceptions of Intelligence and Anthropomorphism Affect Adoption of Personal Intelligent Agents," *Electronic Markets* (31:2), pp. 343–364.

Nunamaker, J., Derrick, D., Elkins, A., Burgoon, J., and Patton, M. 2011. "Embodied Conversational Agent-Based Kiosk for Automated Interviewing," *Journal of Management Information Systems* (28:1), pp. 17–48.

Qiu, L., and Benbasat, I. 2009. "Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems," *Journal of Management Information Systems* (25:4), pp. 145–182.

Rosenthal-Von Der Pütten, A. M., and Krämer, N. C. 2014. "How Design Characteristics of Robots Determine Evaluation and Uncanny Valley Related Responses," *Computers in Human Behavior* (36), pp. 422–439.

Rzepka, C., and Berger, B. 2018. "User Interaction with AI-Enabled Systems: A Systematic Review of IS Research," *International Conference on Information Systems 2018*, pp. 1–17.

Schanke, S., Burtch, G., and Ray, G. 2021. "Estimating the Impact of 'Humanizing' Customer Service Chatbots," *Information Systems Research* (32:3), pp. 736–751.

Schroeder, J., and Schroeder, M. 2018. "Trusting in Machines: How Mode of Interaction Affects Willingness to Share Personal Information with Machines," in *Proceedings of the Annual Hawaii International Conference on System Sciences*, pp. 472–480.

Schuetz, S., and Venkatesh, V. 2020. "The Rise of Human Machines: How Cognitive Computing Systems Challenge Assumptions of User-System Interaction," *Journal of the Association for Information Systems* (21:2), pp. 460–482.

Schuetzler, R. M., Grimes, G. M., and Giboney, J. S. 2018. "An Investigation of Conversational Agent Relevance, Presence, and Engagement," *Americas Conference on Information Systems 2018: Digital Disruption, AMCIS 2018*, pp. 1–10.

Schuetzler, R. M., Grimes, G. M., and Scott Giboney, J. 2020. "The Impact of Chatbot Conversational Skill on Engagement and Perceived Humanness," *Journal of Management Information Systems* (37:3), pp. 875–900.

Seeger, A.-M., Pfeiffer, J., and Heinzl, A. 2021. "Texting with Human-like Conversational Agents: Designing for Anthropomorphism," *Journal of the Association for Information Systems*, Forthcoming.

Seymour, M., Yuan, L., Dennis, A. R., and Riemer, K. 2021. "Have We Crossed the Uncanny Valley? Understanding Affinity, Trustworthiness, and Preference for Realistic Digital Humans in Immersive Environments," *Journal of the Association for Information Systems* (22:3), pp. 591–617.

Siegel, M., Breazeal, C., and Norton, M. I. 2009. "Persuasive Robotics: The Influence of Robot Gender on Human Behavior," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems,* IEEE, pp. 2563–2568.

Sohn, S. 2019. "Can Conversational User Interfaces Be Harmful? The Undesirable Effects on Privacy Concern," in *40th International Conference on Information Systems (ICIS)*.

Wang, S., Lilienfeld, S. O., and Rochat, P. 2015. "The Uncanny Valley: Existence and Explanations," *Review of General Psychology* (19:4), pp. 393–407.

Waytz, A., Heafner, J., and Epley, N. 2014. "The Mind in the Machine: Anthropomorphism Increases Trust in an Autonomous Vehicle," *Journal of Experimental Social Psychology* (52), Elsevier Inc., pp. 113–117.

Xie, L., and Lei, S. 2022. "The Nonlinear Effect of Service Robot Anthropomorphism on Customers' Usage Intention: A Privacy Calculus Perspective," *International Journal of Hospitality Management* (107), p. 103312.

Yang, Y., Liu, Y., Lv, X., Ai, J., and Li, Y. 2021. "Anthropomorphism and Customers' Willingness to Use Artificial Intelligence Service Agents," *Journal of Hospitality Marketing and Management*, Routledge.

Yoganathan, V., Osburg, V. S., H. Kunz, W., and Toporowski, W. 2021. "Check-in at the Robo-Desk: Effects of Automated Social Presence on Social Cognition and Service Implications," *Tourism Management* (85), pp. 261–5177.

Yogeeswaran, K., Złotowski, J., Livingstone, M., Bartneck, C., Sumioka, H., and Ishiguro, H. 2016. "The Interactive Effects of Robot Anthropomorphism and Robot Ability on Perceived Threat and Support for Robotics Research," *Journal of Human-Robot Interaction* (5:2), pp. 29–47.

You, S., and Robert, L. P. 2018. "Emotional Attachment, Performance, and Viability in Teams Collaborating with Embodied Physical Action (EPA) Robots," *Journal of the Association for Information Systems* (19:5), pp. 377–407.

Zhang, S., Meng, Z., Chen, B., Yang, X., and Zhao, X. 2021. "Motivation, Social Emotion, and the Acceptance of Artificial Intelligence Virtual Assistants—Trust-Based Mediating Effects," *Frontiers in Psychology* (12), p. 3441.

Złotowski, J., Yogeeswaran, K., and Bartneck, C. 2017. "Can We Control It? Autonomous Robots Threaten Human Identity, Uniqueness, Safety, and Resources," *International Journal of Human Computer Studies* (100), pp. 48–54.

Appendix

Figure A. Effect of anthropomorphism on users' attitudinal responses.

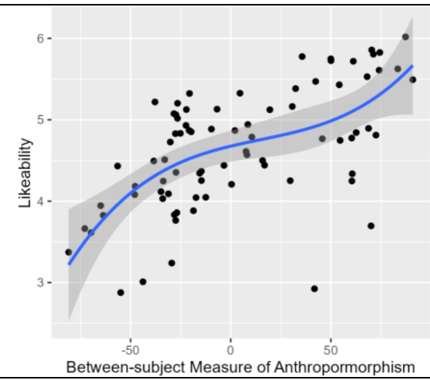

Figure A1. Effect of between-subject anthropomorphism on **likability** (R^2 = 36%)

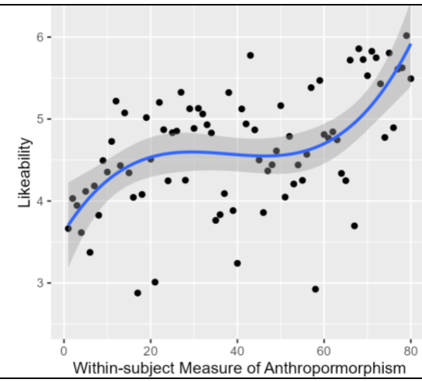

Figure A2. Effect of within-subject anthropomorphism on **likability** (R^2 = 31%)

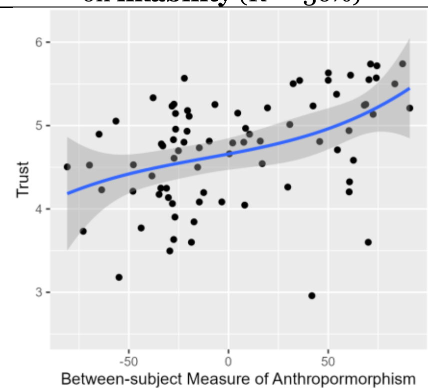

Figure A3. Effect of between-subject anthropomorphism on **trust** (R^2 = 19%)

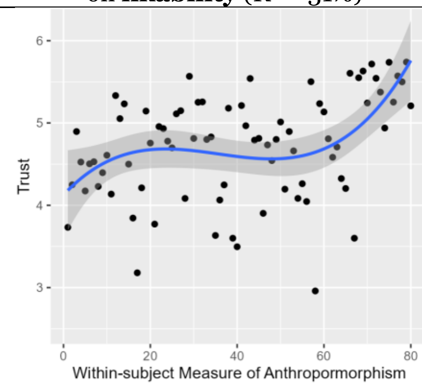

Figure A4. Effect of within-subject anthropomorphism on **trust** (R^2 = 20%)

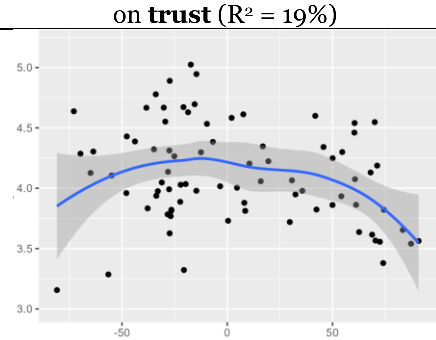

Figure A5. Effect of between-subject anthropomorphism on **risk** (R^2 = 11.5%)

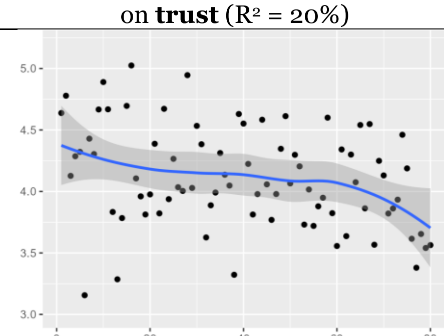

Figure A6. Effect of within-subject anthropomorphism on **risk** (R^2 = 9.3%)

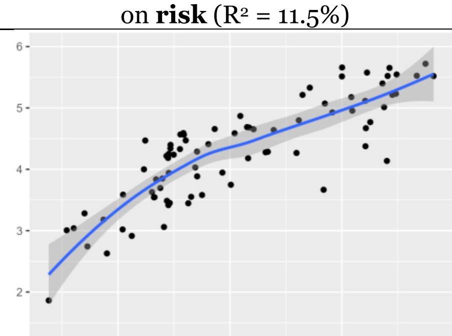

Figure A7. Effect of between-subject anthropomorphism on **social presence** (R^2 = 73.9%)

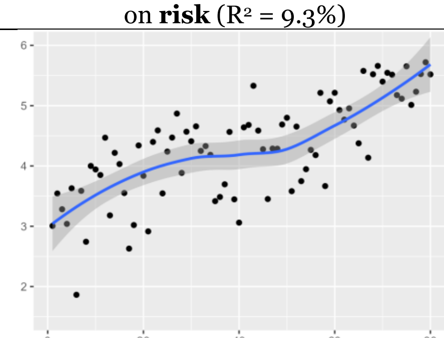

Figure A8. Effect of within-subject anthropomorphism on **social presence** (R^2 = 56.3%)

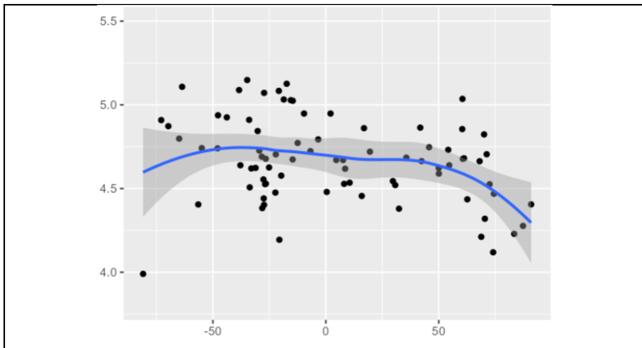

Figure A9. Effect of between-subject anthropomorphism on **privacy invasion** (R^2=15.2%)

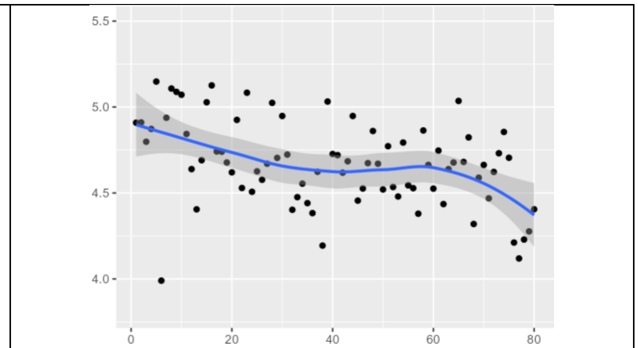

Figure A10. Effect of within-subject anthropomorphism on **privacy invasion** (R^2=20%)

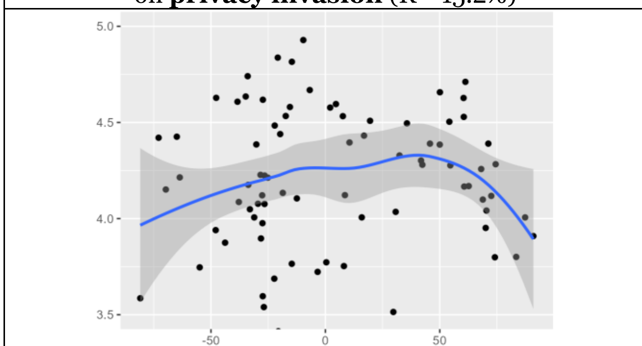

Figure A11. Effect of between-subject anthropomorphism on **realistic threat** (R^2 = 3.7%)

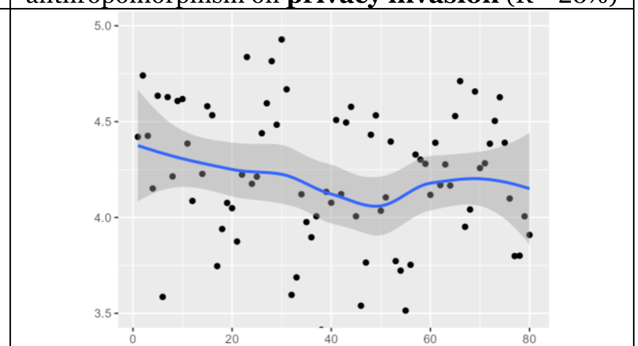

Figure A12. Effect of within-subject anthropomorphism on **realistic threat** (R^2 = 0.7%)

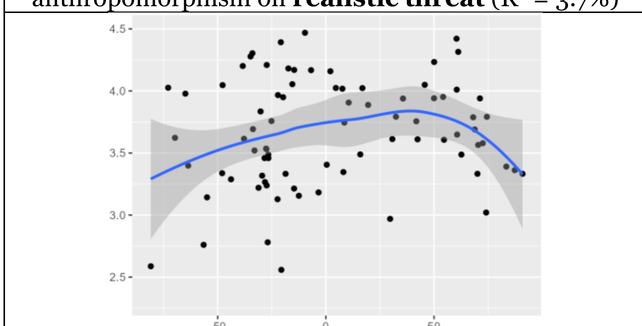

Figure A13. Effect of between-subject anthropomorphism on **identity threat** (R^2 = 5.5%)

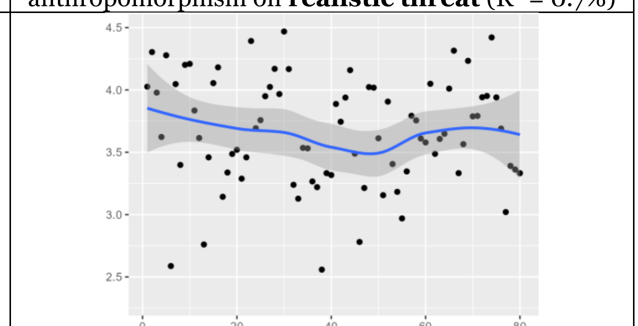

Figure A14. Effect of within-subject anthropomorphism on **identity threat** (R^2 = 0.3%)

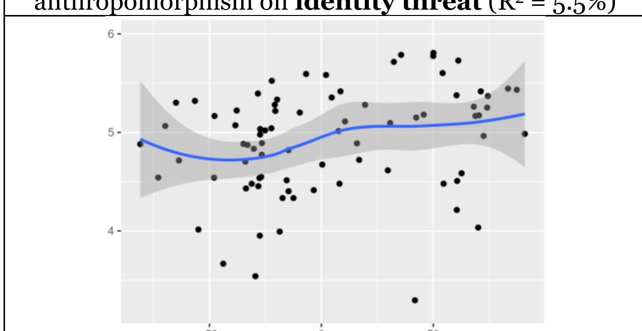

Figure A15. Effect of between-subject anthropomorphism on **usage intention** (R^2 = 6%)

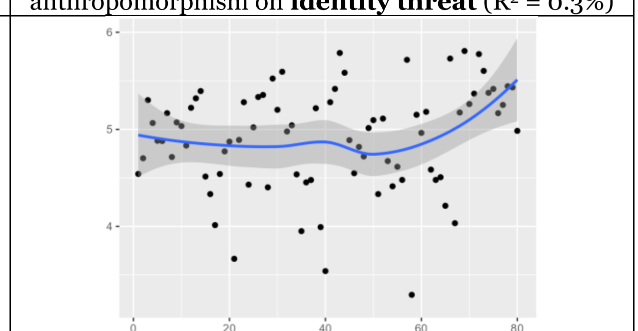

Figure A16. Effect of within-subject anthropomorphism on **usage intention** (R^2 = 6.3%)

Table A. A summary of key attitudinal variables investigated in the past IS studies on AI robots.

Author(s) and year	Journal	Research Method	PE	ATT	SP	TRU	PU	PRI	ANT	PR	FAM	PI	UI	LIK	SAT
Robots with physical presence															
Seymour et al. (2021)	JAIS	Mixed-method approach				×			×		×			×	
Benlian et al. (2020)	ISJ	Multimethod approach						×	×						
You & Robert (2018)	JAIS	Between-subjects experiment		×											
Blut et al. (2018)	ICIS	Video-based experiments							×			×		×	
Nunamaker et al. (2011)	JMIS	Experiment				×			×					×	
Virtual robots															
Schanke et al. (2021)	ISR	Experiment			×				×					×	
Ge et al. (2021)	ISR	Second-hand data analysis					×			×			×		
Seeger et al. (2021)	JAIS	An online experiment							×						
Schuetzler et al. (2020)	JMIS	Experiment			×				×						
Diederich et al. (2020)	ICIS	An online experiment							×						×
Brendel et al. (2020)	*AMCIS*	Experiment										×			×
Danckwerts et al. (2020)	ECIS	Experiment	×		×	×	×						×		
Moussawi & Koufaris (2019)	HICSS	Survey questionnaire					×		×			×	×		×
Bruckes et al. (2019)	ICIS	Experiment				×				×			×		
Sohn (2019)	ICIS	Experiment			×			×							
Schuetzler et al. (2018)	*AMCIS*	Experiment			×				×						
Qiu & Benbasat (2009)	JMIS	Experiment	×		×	×	×		×				×		

Note: PE: perceived enjoyment; ATT: attitude toward robots; SP: social presence; TRU: Trust/trustworthiness; PU: perceived usefulness; PRI: privacy invasion/privacy-related concern; ANT: anthropomorphism; PR: perceived risk; FAM: familiarity; PI: perceived intelligence; UI: usage intention/adoption; LIK: likeability; SAT: satisfaction