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Research article

Customer acceptance of humanoid robots in hotel reception services: A study of future hospitality trends

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ABSTRACT

This study investigates the factors influencing customer acceptance of humanoid robot receptionists in hotels, focusing on how perceived usefulness, social capability, anthropomorphism, perceived intelligence, and cultural norms shape attitudes and adoption intentions. A quantitative survey of 527 hotel guests in Vietnam was conducted using non-probability sampling, and data were analysed using Partial Least Squares Structural Equation Modelling to validate the extended acceptance model. The findings reveal that usefulness, social capability, anthropomorphism, and perceived intelligence significantly enhance customer attitudes toward humanoid robot reception services, and attitudes strongly predict intentions to use such services, with anthropomorphism emerging as the most influential driver. Social and cultural norms strengthen the relationship between attitudes and behavioral intentions, while anxiety toward robots weakens the impact of perceived intelligence, and education shows no significant effect. The study provides practical implications for hotel managers seeking to design effective robot-based reception services that address customer expectations, reduce technology-related anxiety, and improve cultural alignment. The paper contributes novel empirical evidence from an emerging tourism market and introduces an extended model that incorporates social and cultural moderators to explain customers' intentions to engage with humanoid robot receptionists.

KEYWORDS

anthropomorphism;
customer adoption;
hotel reception;
humanoid robots;
human-robot interaction

Introduction

Technological advances have transformed the hotel industry, particularly through the use of humanoid service robots (Begum et al., 2025; Said et al., 2023). They are beneficial during COVID-19 because they help reduce transmission risks (Said et al., 2023; Wan et al., 2021). Besides, by performing tasks quickly and consistently, these robots help reduce operational costs and queuing times, thereby improving customer satisfaction and profitability (Luo et al., 2021). Even though these robots have proved their benefits, there remains a scarcity of insights on usage intentions in the post-pandemic context (Fu et al., 2022). Furthermore, existing research often presents inconsistent findings, making it challenging to identify the most relevant factors of service robot acceptance in hotels (Begum et al., 2025). Their physical appearance matters; if they look too human-like, they may cause discomfort (Wang et al., 2015). However, appearance alone may not fully explain human-likeness effects in human-robot interaction (Song & Kim, 2022), so this study replaces the appearance variable with anthropomorphism to better reflect the psychological depth of consumer-robot engagement in the present context. Additionally, despite their efficiency, robots still lack the empathy and decision-making flexibility that human staff can provide. Besides, the roles of culture and education in shaping individuals' responses to service robots have been underexplored (Filieri et al., 2022). The study

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has attempted to address this gap by incorporating social and cultural norms as well as educational background into the analytical framework. Finally, much of the existing work focuses on countries where consumers may have greater baseline familiarity with robots. Therefore, this study decided to conduct the research in a country at an early stage of adopting service robots to explore the differences. Moreover, Vietnam offers an important but under-researched context for this technology, as it can help address labour shortages and rising costs in the country's growing tourism industry. Building on these gaps, the present study would like to examine how Vietnamese consumers perceive humanoid robot receptionists. The goal is to develop a comprehensive model that helps managers and policymakers in solutions that meet both operational goals and cultural values in emerging markets.

Literature review

Theoretical background

Nass et al. (1994) introduced the Computers-Are-Social-Actors (CASA) theory, which found that users unconsciously apply human social norms and expectations to computers as if they were social beings. Nass & Moon (2000) explain that specific "humanness cues", such as the use of natural language, interactive behavior, and taking on roles typically performed by people, can make users respond to machines as if they were human. For humanoid robot service representatives (RSRs), these cues include their physical appearance, AI-driven abilities, and their capacity to perform tasks associated with human service work (Song & Kim, 2022). Research supports the impact of these cues. (Pelau et al., 2021) found that in the restaurant industry, human-like robots significantly improved customers' perception of the interaction and increased acceptance of the technology. Likewise, de Graaf et al. (2015) showed that people often treat household robots politely and empathetically, confirming the CASA model's idea that humans naturally respond to machines that act or look human. Additionally, Goodrich & Schultz (2008) describe Human-Robot Interaction (HRI) as a field focused on understanding, designing, and evaluating robots that work with or alongside people. In these settings, both the human user and the robot act as active participants in the same environment. Overall, attitudes toward human–robot interaction refer to customers' emotional reactions when engaging with humanoid service robots - reactions shaped by the robots' human-like cues and reflected in how comfortable and satisfied customers feel during the interaction (Song & Kim, 2022).

Literature review and hypotheses development

Usefulness and attitude toward human-robot interaction

Many studies indicate that in computer-mediated environments, consumers are more likely to form positive evaluations of a product or service when they perceive it as applicable (Davis, 1989; Mende et al., 2019). Formally, perceived usefulness is defined as the extent to which an individual believes that using a specific system will improve their job performance (Davis, 1989). In this study, usefulness is defined as the robot's ability to provide hotel services and the level of hotel publicity (Zhong et al., 2020). With respect to the dependent variable, attitude refers to the degree to which a person has a positive or negative evaluation of the target behavior, in this case, the use of humanoid robots in hotels. For instance, Shin & Jeong (2020) observed that hotel guests hold positive attitudes toward robot concierges, which positively influences their intention to reuse such services. Therefore, this study proposes the following hypothesis:

H1a: Usefulness has a positive impact on Attitudes

Social capability and attitude toward human-robot interaction

Users interacting with socially intelligent robots often perceive them as caring and reliable (Song & Kim, 2022). Supporting this, Zhao et al. (2019) highlight that consumers' positive attitudes toward humanoid service robots in HRI arise from the robots' social capabilities, such as consciousness, self-awareness, and emotional expression. Song & Kim (2022) define the variable social capability as the robots' social skills for interacting with people, including interactive communication, approachability, appropriate responses, and listening without interjecting when the customer is speaking. This social engagement enhances the robots' perceived social capabilities and encourages acceptance in service roles such as hotel receptionists. Consequently, robots' ability to engage emotionally strengthens positive consumer attitudes and creates more natural, supportive human-robot interactions. Therefore, this study proposes the following hypothesis:

H1b: Social Capability has a positive impact on Attitudes

Anthropomorphism and attitude toward human-robot interaction

Anthropomorphism is the degree to which consumers perceive service robots as having human-like qualities such as emotions, self-consciousness, and intellect (Della Corte et al., 2023). Social behaviour, compared to purely functional behaviour, tends to increase anthropomorphism toward robots (Roselli et al., 2025), as it is used to explain robots' behaviour toward humans (Fraune et al., 2020). In addition, two studies by Salem et al. (2014) and Yu & Ngan (2019) approached anthropomorphism from the perspective of warmth in interpersonal communication, concluding that the more human-like the robot is, the more readily it is accepted by humans. In addition, anthropomorphism plays a prominent role in influencing customers' behavioural intentions (Begum et al., 2025). The academic literature shows that anthropomorphism is an important antecedent factor that shapes customers' attitudes (Mehmood et al., 2024; Shin & Jeong, 2020). Therefore, this study proposes the following hypothesis:

H1c: Anthropomorphism has a positive impact on Attitudes

Perceived intelligence and attitudes toward human-robot interaction

Begum et al. (2025) define perceived intelligence as the capacity of service robots to apply their prior knowledge and skills in a variety of service contexts, including the hotel sector. Dautzenberg et al. (2024) noted that the level of intelligence in robots is likely to increase as more commercially available research platforms are adopted. Therefore, hotels need to strategically invest in intelligent service robot technology to improve the user experience. In particular, the sensory intelligence of robots relates to their ability to understand and respond to customer needs, suggesting that robots equipped with advanced intelligence can better comprehend and predict, thereby creating a more positive and satisfying experience (Begum et al., 2025). There is a broad consensus that this factor can influence consumers' intention to use service robots in the hotel environment (Kim et al., 2022; Mehmood et al., 2024; Song & Kim, 2022). Therefore, this study proposes the following hypothesis:

H1d: Perceived Intelligence has a positive impact on Attitudes

Attitudes toward human-robot interaction and customer adoption of robots

Customer adoption refers to the time and effort people are willing to invest in attempting and executing a specific behaviour (Kim & Woo, 2016). In this context, this variable indicates the degree to which an individual is ready to interact with the hotel's humanoid robot receptionist. Zhong et al. (2020) found that a positive attitude toward using service robots positively affects customers' willingness to accept hotel robots. Additionally, this relationship is further explained by the role of anthropomorphism in enhancing positive attitudes, which, in turn, increases acceptance (Said et al., 2023). Therefore, this study proposes the following hypothesis:

H2: Attitudes toward Human-Robot Interaction have a positive impact on Customer Adoption.

Social and Cultural Norms, Attitudes toward Human-Robot Interaction, and Customer Adoption of Robots

Social and cultural norms govern what is considered acceptable or unacceptable behavior in interpersonal interactions. Shehawy et al. (2025) found that the impact of attitude on the intention to adopt service robots depends on various social and cultural norms. Indeed, some people have more positive perceptions of humanoid robots than of non-humanoid robots, as cultural values can shape how people perceive robot appearance (Shehawy et al., 2025). Moreover, people’s attitudes toward adopting service robots may be influenced by how they believe others in their social or cultural group will view them (Said et al., 2023). Therefore, this study proposes the following hypothesis:

H3: Social and cultural norms moderate the relationship between the Attitude and Customer Adoption

Education, attitudes toward human-robot interaction, and customer adoption of robots

Education significantly influences how people accept robots. Research shows that individuals with higher levels of education are more willing to adopt these robots (Roozen et al., 2023). They are more likely to view robots as competent and are better at understanding both the benefits and risks of new technologies. Then, consumers can make more informed decisions (Szczepanowski et al., 2020). Therefore, this study proposes the following hypothesis:

H4: Education moderates the relationship between the Attitude and Customer Adoption.

Anxiety toward robots, usefulness, and attitudes toward human-robot interaction
Robot-related anxiety, which is caused by past experiences, fear, or media influence, often leads people to avoid new technologies (Celik & Yesilyurt, 2013). When customers perceive safety, privacy, or robot performance concerns, they may view robots as less valuable. Then, it can lead to more negative attitudes toward interacting with them. Studies show that anxiety weakens the positive impact of perceived usefulness on attitudes toward robots (Song & Kim, 2022). Although this effect can vary when robots become more human-like (Yoganathan et al., 2021), high anxiety generally reduces positive reactions. Therefore, this study proposes:

H5a: Anxiety toward robots moderates the relationship between Usefulness and Attitudes

Anxiety toward robots, social capability, and attitudes toward human-robot interaction
Consumers' pre-existing anxiety toward robots can evoke discomfort and uncertainty, shaping negative attitudes toward HRI (Song, 2017). In addition, Song & Kim (2022) found that in hotel and retail service contexts, consumers with high anxiety toward robots often questioned their social abilities. Hence, they perceive themselves as lacking awareness of social cues or making interactions feel awkward. In contrast, customers with lower anxiety were more receptive to socially capable robots and formed more positive attitudes toward HRI. Therefore, this study proposes the following hypothesis:

H5b: Anxiety toward robots moderates the relationship between Social Capability and Attitudes

Anxiety toward robots, anthropomorphism, and attitudes toward human-robot interaction
Prior studies have reported inconsistent findings regarding the effect of anthropomorphism on user attitudes. This suggests that individual factors may moderate the relationship between anthropomorphism and attitudes (Lu et al., 2019; Zhang et al., 2021). Furthermore, Nomura, Kanda et al. (2008) also found that consumers with higher anxiety toward robots tend to feel discomfort or eeriness when interacting with human-like robots. Therefore, this study proposes the following hypothesis:

H5c: Anxiety toward robots moderates the relationship between Anthropomorphism and Attitudes

Anxiety toward robots, perceived intelligence, and attitudes toward human-robot interaction
Individuals who experience higher levels of anxiety toward robots are generally more likely to hold negative attitudes and show less willingness to engage with them. Therefore, even if a robot is perceived as intelligent, an individual's acceptance of and attitude toward HRI still depends on their anxiety level (Abbasi et al., 2023). In this sense, robot anxiety serves as a moderating factor, affecting the relationship between perceived robot intelligence and consumer attitudes in hotel settings. Therefore, this study proposes the following hypothesis:

H5d: Anxiety toward robots moderates the relationship between Perceived Intelligence (PI) and Attitudes

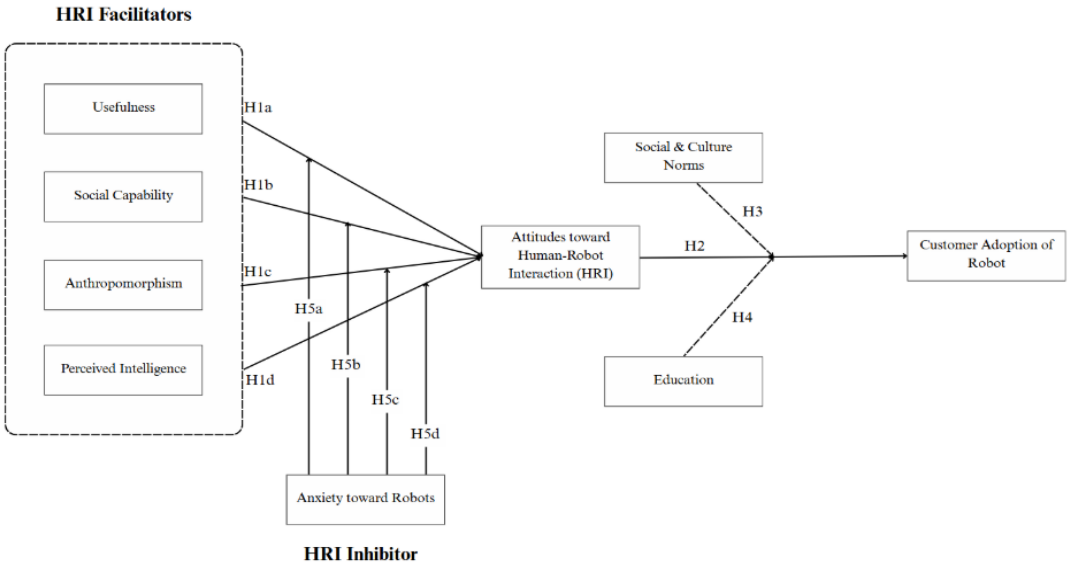

Figure 1: Research model

Methodology

According to the quota method, the research adopted control attributes to determine the number of elements to ensure the proportion. Specifically, qualitative interviews revealed differences in the degree of Vietnamese consumer acceptance, driven by attitudes and HRI facilitators, which in turn led to behavioral intentions among students, undergraduates, and working people. Therefore, in this study, job attributes are used to allocate the survey respondents. For the convenience sampling method, key respondents who are the easiest individuals to access are selected and answer questions on the survey sheet based on their relationships and experiences. However, it is considered a sampling bias, so before reaching the target population, the questionnaires are distributed over various time periods and locations. To achieve the target sample size of n = 527, the study used Google Forms as a sampling technique. A 7-point Likert scale was employed, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Specifically, Usefulness (UN), Social Capability (SOC), Anxiety toward robots (AXT), and Attitudes (ATT) were based on Song & Kim (2022). Anthropomorphism (AN) was adapted from Della Corte et al. (2023), and Perceived Intelligence (PI) from Song & Kim (2022). Items measuring Social & Culture Norms (SCN), Education (EDU), and Customer Adoption (CAR) were derived from Shehawy et al. (2025). Moreover, the sampling strategy involved selecting a non-probability sample targeting hotel guests aged 18 and above in Vietnam who are aware of technological trends but unfamiliar with humanoid robots in reception roles. Therefore, the following methods were used: (1) Using Facebook Messenger, where the participants referred others who met the criteria to support the snowball sampling; and (2) Distributing the survey link in relevant Facebook groups for people interested in innovative hotel services.

Results

Sample characteristics

Most respondents were female (54.5%), primarily in the 18-25 age group (48.0%). A significant proportion (45%) of respondents have a university education, indicating that the majority are relatively well educated. Concerning occupation, students make up the largest segment, accounting for 60%, followed by office workers and public employees, each representing 20.1% and 8% respectively. At the same time, freelancers and other occupations are less common. For income level, the largest group of respondents (60%) earns under 10 million VND.

Tables 1. Profile of respondents

Sample Information		Frequency	Percentage (%)
Gender	Male	240	45.5
	Female	287	54.5
Age group	From 18 to 25 years old	253	48.0
	From 25 to 35 years old	127	24.1
	From 35 to 45 years old	121	23.0
	Over 45 years old	26	4.9
Educational Level	12/12 or lower level	150	28.5
	College/University	237	45.0
	Master	105	19.9
	PhD	20	3.8
	Other	15	2.8
Occupation	Freelancer	37	7.0
	Student	316	60.0
	Public employee	42	8.0
	Office worker	106	20.1
	Other	26	4.9
Income	Under 10 million VND	316	60.0
	10 million - 15 million VND	79	15.0
	Over 15 million VND	132	25.0

Testing the quality of observed variables

According to Hair et al. (2014), outer loading values should exceed 0.7. Indicators with loadings between 0.4 and 0.7 may be removed if their exclusion improves CR and AVE. As shown in Table 2, all observed variables exhibit outer loading above 0.7, indicating strong indicator reliability. Additionally, all interaction terms have VIF values below 1.3, suggesting that multicollinearity is not a concern.

Table 2. Outer loading analysis

	AN	ANxAXT	ATT	ATTxSCN	AXT	CAR	PI	PIxAXT	SCN	SOC	SOCx AXT	UN	UNx AXT
AN x AXT		1.101											
AN1	0.791												
AN2	0.787												
AN3	0.746												
AN4	0.762												
ATT x SCN				1.193									
ATT1			0.804										
ATT2			0.811										
ATT3			0.758										
AXT1					0.777								
AXT2					0.828								
AXT3					0.724								

	AN	ANxAXT	ATT	ATTxSCN	AXT	CAR	PI	PIxAXT	SCN	SOC	SOCx AXT	UN	UNx AXT
AXT4					0.764								
AXT5					0.772								
CAR1						0.795							
CAR2						0.782							
CAR3						0.823							
PI x AXT								1.156					
PI1							0.793						
PI2							0.847						
PI3							0.808						
SCN1									0.804				
SCN2									0.834				
SCN3									0.820				
SOC x AXT											1.199		
SOC1										0.801			
SOC2										0.748			
SOC3										0.752			
SOC4										0.760			
SOC5										0.780			
UN x AXT													1.209
UN1												0.769	
UN2												0.748	
UN3												0.735	
UN4												0.794	
UN5												0.746	

Internal consistency reliability - Cronbach's alpha

A Cronbach's Alpha value ranges from 0 to 1, with higher values indicating stronger internal consistency. Values above 0.9 are considered excellent, values above 0.8 are considered good, and values above 0.7 are considered acceptable (Quansah, 2017). In Table 3, all variables exceed the acceptable threshold of 0.7, confirming that the measurements used in this research are acceptable.

Table 3. Cronbach's Alpha result

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
UN	0.816	0.819	0.871	0.576
SOC	0.827	0.830	0.878	0.591
AN	0.774	0.777	0.855	0.595
PI	0.751	0.760	0.857	0.666
AXT	0.832	0.835	0.882	0.599
ATT	0.701	0.702	0.834	0.626
SCN	0.756	0.757	0.860	0.672
CAR	0.719	0.721	0.842	0.640

Composite reliability

Composite reliability assesses internal consistency. In general, composite reliability (CR) values ranging from 0.7 to 0.9 are acceptable. The results in Table 3 show that all constructs (rho_a and rho_c) fall between 0.7 and 0.95, indicating strong reliability and supporting the validity of the measurement scales.

The average variance extracted (AVE)

The AVE reflects the average amount of variance that a construct captures from its indicators, relative to the amount due to measurement error (Hair & Alamer, 2022). An AVE value above 0.5 is generally seen as acceptable, as it suggests the construct captures enough of the indicators' variance to be considered reliable (Hair et al., 2014). According to Table 3, all constructs in the study have AVEs exceeding 0.5, indicating that each construct explains more than half of the variance in its observed indicators. This result meets the requirement for convergent validity and confirms that no construct falls below the acceptable standard.

Discriminant validity

Discriminant validity is ensured when the square root of the AVE for each latent variable is higher than all the correlations between the latent variables (Fornell & Larcker, 1981). In this study, the HTMT criterion was used to assess discriminant validity. As shown in Table 4, all HTMT values are less than 0.9, indicating that discrimination is guaranteed (Henseler et al., 2015).

Table 4. Discriminant validity results

	AN	AN x AXT	ATT	ATT x SCN	AXT	CAR	PI	PI x AXT	SCN	SOC	SOC x AXT	UN	UN x AXT
AN													
AN x AXT	0.397												
ATT	0.675	0.420											
ATT x SCN	0.410	0.508	0.490										
AXT	0.354	0.307	0.644	0.477									
CAR	0.391	0.361	0.697	0.430	0.487								
PI	0.369	0.336	0.600	0.443	0.473	0.525							
PI x AXT	0.314	0.419	0.524	0.484	0.396	0.482	0.382						
SCN	0.435	0.341	0.586	0.506	0.430	0.423	0.448	0.374					
SOC	0.436	0.382	0.694	0.479	0.455	0.499	0.376	0.370	0.448				
SOC x AXT	0.363	0.556	0.476	0.503	0.384	0.405	0.376	0.468	0.388	0.360			
UN	0.440	0.384	0.631	0.475	0.459	0.482	0.487	0.443	0.493	0.453	0.417		
UN x AXT	0.357	0.529	0.564	0.543	0.459	0.481	0.442	0.553	0.402	0.410	0.618	0.476	

Path coefficient

In Table 5, the bootstrap sample means are closely aligned with the original sample values, and many path coefficients are statistically significant at the 95% confidence level ($p < 0.05$). Therefore, seven hypotheses are supported. These include H1a, H1b, H1c, and H1d, confirming that core HRI facilitators significantly enhance user attitudes toward robots (ATT). Among them, AN has the most decisive influence ($\beta = 0.241$). (H2) is also supported and shows the most significant impact ($\beta = 0.396$), underscoring that ATT is a key factor influencing adoption behaviour (CAR). The moderating effect of SCN ($\beta = 0.143$, $p = 0.000$) is supported, suggesting that SCN influences the translation of ATT into adoption behaviour. Among the AXT-related moderating variables, only H5d is supported. Education (EDU) (H4) was modelled as a continuous moderator for simplicity and statistical power while recognizing the ordinal nature. However, it is not supported ($p = 0.404$), suggesting that educational background does not alter how attitudes affect adoption.

Table 5. Results of testing research hypotheses

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Conclusion
H1a: UN → ATT	0.120	0.121	0.035	3.416	0.001	Supported
H1b: SOC → ATT	0.240	0.239	0.032	7.451	0.000	Supported
H1c: AN → ATT	0.241	0.243	0.032	7.614	0.000	Supported
H1d: PI → ATT	0.127	0.129	0.037	3.461	0.001	Supported
H2: ATT → CAR	0.396	0.396	0.044	8.925	0.000	Supported
H3: ATT x SCN → CAR	0.143	0.141	0.034	4.249	0.000	Supported
H4: ATT x EDU → CAR	-0.032	-0.032	0.042	0.836	0.404	Not Supported
H5a: UN x AXT → ATT	0.076	0.074	0.040	1.899	0.058	Not Supported
H5b: SOC x AXT → ATT	0.013	0.014	0.031	0.406	0.685	Not Supported
H5c: AN x AXT → ATT	-0.035	-0.036	0.037	0.967	0.334	Not Supported
H5d: PI x AXT → ATT	0.085	0.084	0.038	2.244	0.025	Supported

Slope analysis

Based on the foundational guidelines provided by Dawson (2014), the simple slope plot was used to visualize the interaction pattern between ATT and CAR across different levels of education. Figure 2 below suggests that ATT is positively associated with CAR at all levels of education. However, these patterns should be interpreted with caution because the moderating effect of education was not statistically significant ($p=0.404$). Therefore, the plot is presented for descriptive purposes and does not provide evidence that the ATT-CAR relationship differs significantly across educational levels.

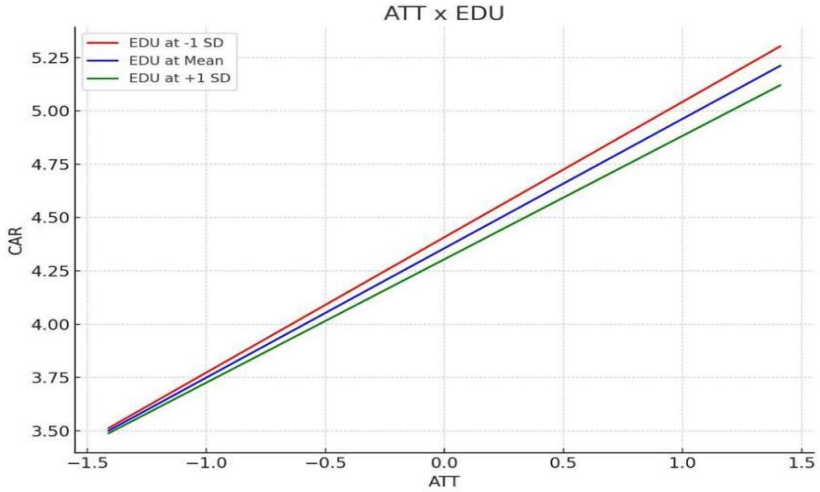

Figure 2: Slope analysis for the moderation between education, attitude, and customer adoption of robots

Discussion

The positive effects of the four HRI facilitators, including Usefulness (UN), Social Capability (SOC), Anthropomorphism (AN), and Perceived Intelligence (PI), on Attitudes (ATT) are consistent with earlier findings by Song & Kim (2022) and Begum et al. (2025). However, unlike prior studies that highlighted intelligence as the main factor, Vietnamese customers emphasize Anthropomorphism and Social Capability. Meanwhile, the results also show a strong relationship between Attitudes (ATT) and Customer Adoption (CAR) (Shehawy et al., 2025; Song & Kim, 2022). When customers feel good about robot receptionists, they are more likely to accept and use them (Roozen et al., 2023; Seyitoğlu et al., 2021). Social and Cultural Norms (SCN) are found to positively moderate the relationship between Attitude and Adoption, contrary to Shehawy et al. (2025). In this study, attitude has a more substantial effect on adoption when customers place

greater emphasis on cultural factors. This means robots should be designed to fit local culture in their behaviour, gestures, and appearance (Huang et al., 2021). Moreover, the research highlights that levels of education do not influence attitudes or customer acceptance, which is inconsistent with the findings of Shehawy et al. (2025). This research also underscores a significant finding: anxiety toward robots strengthens the effects of perceived intelligence on consumers' attitudes. If the robot appears intelligent, it helps reduce anxiety and foster a positive attitude, which aligns with the research by Song & Kim (2022). In contrast, this research did not find sufficient evidence to support the moderating role of anxiety toward robots in the relationship between perceived usefulness, social capability, and anthropomorphism and attitudes toward HRI, contradicting the findings of Song & Kim (2022) and Della Corte et al. (2023).

Conclusions and managerial implications

By applying the CASA model to humanoid robot receptionists and extended Human-Robot Interaction (HRI) facilitators, the study enriches the existing literature by examining the in-depth relationships between key HRI variables, including Usefulness (UN), Social Capability (SOC), Anthropomorphism (AN), Perceived Intelligence (PI), and their influence on Attitudes toward Human-Robot Interaction (ATT) and Customer Adoption of Robot (CAR). Applying the CASA model to humanoid robot receptionists in Vietnamese hotels, this study shows how four factors: Usefulness, Social Capability, Anthropomorphism, and Perceived Intelligence, shape both customer attitudes (ATT) and their intention to adopt (CAR). Similar to Song & Kim (2022), which find that all four factors play an important role in shaping positive attitudes toward robot receptionists. Specifically, this study reveals that customers tend to be more cautious and less comfortable with robots that have lower social capability. However, the study's results contrast with those of Begum et al. (2025), who emphasized Perceived Intelligence as the key driver. Instead, the results reveal that anthropomorphism is the strongest factor influencing Vietnamese customers' willingness to adopt robot receptionists. By demonstrating that human-like characteristics significantly enhance users' behavioural intentions, this research extends CASA theory. It offers valuable insights for future research on artificial intelligence, consumer behaviour, or sustainable development. As humanoid robots become more common in hotels, it is important to understand how consumers respond to them and what influences their willingness to engage with them (de Graaf et al., 2015). Based on the above findings, this study identifies several practical implications for hospitality managers and service designers. First, while Song & Kim (2022) emphasized intelligence, it shows that Vietnamese consumers respond more positively to robots that appear warm, expressive, and socially interactive. Therefore, hotels should prioritize friendly gestures and speak naturally when selecting robots. Moreover, anxiety toward robots influences how customers interpret a robot's intelligence, so a robot that performs tasks smoothly and communicates effectively can help reduce discomfort and build trust. It is also important to invest in reliable, well-programmed robots for everyday tasks. Overall, by focusing on design and emotional comfort, Vietnamese hotels can introduce humanoid robots to appeal to a wide range of consumers in the future. Despite valuable insights, this study still contains a few notable limitations. Firstly, the study was conducted within a limited geographical scope, focusing only on consumers in Vietnam. Hence, future research should broaden the sample to include participants from various geographic areas and socio-economic backgrounds across Vietnam or other Southeast Asian countries for comparative analysis. Secondly, the primary data were collected through a cross-sectional survey, so it is advisable to adopt longitudinal methods to track changes in perceptions and behaviors over time. Thirdly, future work can provide deeper insight into which consumer segments are more receptive to humanoid robot receptionists by exploring additional moderating variables, such as prior technology experience or personality traits. Fourthly, while this research investigated a general category of humanoid robots, it did not differentiate between types (e.g. Humanoid vs. non-humanoid, static vs. mobile robots), which may generate different consumer reactions. Future research could explore how specific robot designs and functions influence consumer responses. Lastly, future research should integrate barriers and inhibitors into acceptance models to present a more balanced view, because this study did not delve into the negative psychological factors that may reduce the likelihood of adoption, such as fear of job replacement, privacy concerns, or the 'uncanny valley' effect (Mori et al., 2012).

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