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Trust me, I'm a robot: relational determinants of social robot acceptance among university students

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Abstract

Purpose – Although social robots are increasingly being used in higher education, the relational antecedents of students' acceptance of these robots remain unexplored. This study re-conceptualises the technology acceptance model (TAM) for social robots by shifting the theoretical focus from utilitarian beliefs toward the relational quality of the human–robot interaction (HRI), positioning trust, satisfaction and rapport as main relational antecedents of students' attitudes and behavioural intentions toward social robots. The study also examines the moderating effects of user motivation, empathy, risk aversion and technology readiness on the attitude–behavioural intention relationship.

Design/methodology/approach – Cluster sampling was used to define the sample, which comprised 900 university students from six public universities in Greece. Structural equation modelling (SEM) was conducted with AMOS 29 to test the proposed model.

Findings – Trust, satisfaction and rapport are strong positive predictors of student attitude toward social robots, which in turn positively influences students' behavioural intention to use social robots. User motivation, empathy and technology readiness motivators (optimism and innovativeness) strengthen the relationship between attitude and behavioural intention towards social robots, while risk aversion and technology readiness inhibitors (discomfort and insecurity) attenuate this relationship.

Research limitations/implications – Despite the contributions achieved here, there are some limitations that deserve to be mentioned and suggest promising paths for future research. Because this research used a cross-sectional design, it does not allow for causality and the possibility to observe how attitudes and intentions towards social robots develop over time. Future studies with longitudinal designs are needed to test whether the identified antecedents for establishing a relationship with social robots (i.e. trust, satisfaction, rapport) can increase or decrease with repeated social robot interactions (Donnermann *et al.*, 2022).

Practical implications – Given the tight connection of trust, satisfaction and rapport with students' perceptions, it is important that institutions also consider the quality of the HRI when deciding whether or not to use social robots as teaching assistants. This includes the robots' ability to build trust through reliable behaviour, provide satisfaction through responsive interaction and achieve rapport through attentive, empathic and positive communication (Buhmann *et al.*, 2026; Lemon and Dhanesh, 2026).

Originality/value – This study adds to the literature by being one of the first to conceptualise social robot acceptance as a relational phenomenon, positioning trust, satisfaction and rapport as core antecedents of attitude and behavioural intention, a theoretical move entirely absent from existing social robot acceptance and educational HRI research. Beyond the direct effects, this study introduces two theoretically grounded categories of individual-level moderators: psychological-relational moderators (motivation, empathy and risk aversion) and technology-related moderators (technology readiness), which collectively provide a coherent and empirically novel account of the boundary conditions governing social robot acceptance among university students.

Keywords Satisfaction, Rapport, Trust, Attitude, Behavioural intention

Paper type Research article

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1. Introduction

Higher education is becoming a technology-intensive and experience-driven field due to the rapid adoption of artificial intelligence throughout service industries. In order to boost student engagement, expedite support services and bolster institutional competitiveness in a quickly changing educational marketplace, universities are investing more in AI-enabled technologies, such as social robots. The integration of artificial intelligence into higher education systems not only improves the teaching process, administrative functions and promotional strategies, but also radically transforms learning experiences (Horng *et al.*, 2025). Understanding how prospective students evaluate and accept these AI-based technologies is vital for educational institutions aiming to enhance their competitiveness and performance. The integration of artificial intelligence into educational systems is transforming learning and operations by tailoring educational pathways for individual learners (Hu *et al.*, 2025), automating administrative tasks and improving curricula, promoting student engagement and ultimately enhancing the capabilities and accessibility of educational institutions. Among the most promising aspects of this technological transition, social robots are emerging as particularly significant factors, transcending the limits of traditional artificial intelligence by introducing a substantially human, relational dimension to the learning experience (Mahr *et al.*, 2025). Thus, the use of social robots in higher education represents a strategic institutional communication practice that shapes stakeholder relationships, the institutional reputation and the students' acceptance of technological innovation (Buhmann *et al.*, 2026; Chugh *et al.*, 2023).

Social robots are autonomous agents that can communicate with humans using natural language, social signalling, and emotions (Horng *et al.*, 2025). Notable humanoid robots include Pepper (Alhmiedat *et al.*, 2023; Guggemos *et al.*, 2020), with emotional intelligence and natural language processing, and NAO, widely used as a classroom assistant robot in educational settings worldwide (Robaczewski *et al.*, 2021; Woo *et al.*, 2021), as well as AV1, a telepresence robot designed to support students who are unable to attend in person (Turner *et al.*, 2026; Johannessen *et al.*, 2023). Nowadays, social robots are increasingly being utilized in educational contexts as pedagogical agents, teaching assistants, information assistants or navigation assistants. Nonetheless, it is important to distinguish social robots from common forms of educational technology that rely on a screen or interface, since social robots may work through physical, affective and relational cues (Gao *et al.*, 2025). In higher education, recent studies have highlighted how the quality of learning, characterized by trust, engagement and mutual responsiveness, is important in determining student's motivation, persistence and academic performance (Belpaeme *et al.*, 2018). The structural conditions under which these attempts take place, such as increasing ratios of students to staff across the higher education landscape, a growing demand for individualized learning and increasing need to prepare graduates for an AI-augmented workforce, render these attempts not only interesting but urgent. As such, the question is no longer whether social robots belong to higher education but rather what factors affect students to accept them. Unlike conventional educational technologies, social robots are inherently relationship-based agents, whose acceptance is shaped by both beliefs regarding their functionality, and by the quality of the human–robot relationship itself (Horng *et al.*, 2025; Gao *et al.*, 2025).

The acceptance of social robots can best be explored with the Technology Acceptance Model (TAM), which was introduced by Davis (1985) based on the Theory of Reasoned Action. This model suggests that two cognitive beliefs impact technology acceptance;. perceived usefulness, that is defined as the degree to which the user believes that using the technology will improve their performance, and perceived ease of use, defined as the degree to which the user believes that the technology will be free from effort (Gao *et al.*, 2025; Davis, 1985). These two beliefs are used to predict the user's attitude toward a technology, which in turn predicts the user's intention to use the technology (Skandali *et al.*, 2026).

Previous studies using TAM to investigate social robots' acceptance in education have extensively relied solely on the functional antecedents of social robots, perceived usefulness

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and perceived ease of use (Said *et al*., 2023), whereas the relational antecedents such as trust, satisfaction and rapport have been largely ignored, despite being more relevant to agents that are designed for social interaction (Premathilake *et al*., 2025). This is even more obvious for higher education, since a social robot is not just a tool, it is placed in a pedagogical context where a relationship is established. A productivity tool or diagnostic system may be accepted or rejected based on its function. A social robot as a classroom teaching assistant will not be so easily accepted or rejected. For social robots to be accepted by students, the students should interact positively with them and should respond positively to their social signals in a manner that evaluates the interaction in terms of its quality rather than in terms of its functional outcomes. Although perceived usefulness and perceived ease of use are important, other determinants of acceptance are trust, satisfaction and social rapport (Gao *et al*., 2025). From a corporate communication view, trust, satisfaction and rapport are antecedents to technology adoption and at the same time the core dimensions of Stakeholder Relationship Quality (SRQ) as understood in the Relationship Management Theory (Ledingham and Bruning, 2000). When the university employs a social robot as a teaching assistant, the robot functions as an embodied institutional communication agent that mediates the institution–student relationship. This human–robot interaction (HRI) quality operation (trust, satisfaction, rapport) also has a meaningful impact on the institution–stakeholder relationship quality and is relevant for student engagement, institutional reputation, and communication management (Plaisance, 2023;Cornelissen, 2020). Hence, this study extends corporate communication literature by adapting the Relationship Management Theory to the case of robot-assisted institutional communication, an increasingly common type of communication where the HRI quality acts as a predictor for the institution–stakeholder relationship quality. To address this research gap, the current study postulates that trust, satisfaction and rapport could be considered as key relational determinants in the proposed extended TAM model for users' intention to use robots. This study explores the impact of these determinants, which influence higher education students' attitude and intention to use social robots.

In the following sections of the paper, we first present the literature review that drove our research hypotheses development. We then describe our research methodology and the main findings of our data analysis. Finally, we provide a comprehensive discussion and illustrate our study's main theoretical and practical contributions.

2. Theoretical conceptualization and hypotheses

2.1 Relational antecedents of social robot acceptance

Trust in HRI is generally perceived as a cognitive, affective and behavioural phenomenon, including the assessment of robot ability and trustworthiness, the affective reaction towards the robot and the willingness to act on trust. Compared to trust in customary automation, trust in social robots involves higher relational costs and risks, as social robots are often semi-autonomous agents capable of interacting in dynamic and open environments and performing behaviours where the outcome and nature are uncertain (O'Neil and Vasquez, 2026).

Yet, trust is not the only relational dimension that users draw upon to evaluate and orient themselves toward a social robot. Once trust is established, the quality of the interaction and the extent to which the robot meets/exceeds the user's expectations become equally important. Satisfaction is an important service management variable as it directly affects customer loyalty, repeat usage and profitability. According to Oliver's (1999) expectancy-disconfirmation theory of satisfaction, satisfaction occurs when the actual service performance exceeds the expected service performance. A negative disconfirmation of expectations decreases subsequent intentions to use and triggers protective behaviour. As many expectations towards social robots are media-based rather than experience-based, the expectancy–disconfirmation gap in this domain is larger than in conventional educational technologies. In education, satisfaction with social robots is associated with favourable attitudes and improved learning outcomes. When learners feel satisfied with their experiences with a social robot, they are more likely to exhibit

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positive attitudes and intentions toward future use of the robot. As such, satisfaction can be considered as a relational antecedent of behavioural intention in educational HRI.

Besides trust and satisfaction, rapport is a third and arguably more social, dimension of the human robot relationship. While trust is the cognitive-affective orientation of the user toward the robot's trustworthiness, and satisfaction is the evaluative consequence of HRI, rapport is the relational property of HRI; namely, the mutual patterns of attention, positive affect and coordination that develop over periods of time.

Rapport is an important predictor of customer loyalty and other relational outcomes in the service sector, and is increasingly studied in HRI (Song *et al*., 2024). Reciprocity and self-disclosure are two important rapport-generating mechanisms. Thus, social robots with open conversational styles which encourage humans to disclose personal information create a much stronger rapport than robots with task-oriented styles (Sprecher *et al*., 2013).

Rapport is also shaped by non-verbal rapport cues (e.g. mimicking someone's level of body posture, prosody or gestures) that may not result from verbal exchanges. In educational HRI, rapport is essential for engagement and learning and has been identified as an important moderator between social robot deployment and user experience or satisfaction (Borghi *et al*., 2023). This shows that rapport is not a mere segment of functional performance, but is a key relational aspect that influences and shapes the entire acceptance process.

2.2 Trust and attitude

In HRI, trust is defined as a subjective judgment that the human makes of the HRI partners based on the cognitive/emotional dimensions that characterize the two agents. Several studies provide evidence showing that trust is related to intention to use and user acceptance (Della Corte *et al*., 2023). Specific positive characteristics of trust that led to user intention to use and user acceptance of robots include reliability, task performance according to user requirements and friendliness of the robotic social agent (Nertinger *et al*., 2024).

To date, no study has examined how trust is associated with users' attitudes towards robots. In the educational domain, research has focused on how students experience positive learning situations with social robots, the learning outcomes of using social robots and the task of increasing students' interactions with social robots (Shiomi *et al*., 2021). Because trust in social robots is positively correlated with intention to use social robots, it is expected that trust is positively correlated with attitudes toward social robots. This is based on the TAM, which states that attitudes toward a technology are positively correlated with the intention to use that technology. Thus:

H1. Trust in social robots positively influences users' attitudes towards robots.

2.3 Satisfaction and attitude

User satisfaction is one of the most investigated constructs in service management, because of its argued importance on the success of the organization and continuance of the service (Agag *et al*., 2024). Building on Oliver's (1999) expectancy-disconfirmation framework, satisfaction arises when a product or service meets or exceeds user expectations, generating positive evaluative responses that shape future behavioural intentions.

In the context of social robots, satisfaction is positively related with anthropomorphism, interaction, imitation and attitudes toward social robots (Polyportis and Pahos, 2024). In this sense, it could be argued that since user satisfaction characteristics are positively correlated with attitudes toward social robots, user satisfaction with social robots will have a positive impact on user attitudes toward social robots. Nevertheless, satisfaction and attitude have only been mainly studied as concurrent outcomes, without testing the satisfaction-attitude path in the context of TAM (Borghi *et al*., 2023).

In educational settings, student satisfaction is a very important parameter for an effective educational process. While limited evidence supports a direct relationship between trust and attitudes towards social robots, expectancy-disconfirmation theory by Oliver (1999) posits that

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users who are satisfied with a technology will produce more favourable evaluative responses toward it. Thus, it can be concluded that students who are satisfied with the use of social robots in their learning will show a higher favourable attitudinal evaluation of their use. Thus:

H2. Satisfaction from social robots positively influences users' attitudes towards robots.

2.4 Rapport and attitude

Rapport is the quality of a relationship characterized by mutual attentiveness, positivity and coordination. Within the domain of HRI, rapport has been defined as the consumer's perception of a pleasant interaction with a service robot, as well as a personal connection between the customer and the robot (Gremler and Gwinner, 2000) . In the service robot acceptance literature, rapport, alongside the service robot acceptance model's (sRAM) factors of trust and satisfaction, has been studied as a relational antecedent to robot acceptance (Song *et al.*, 2024) . Rapport building, through self-disclosure reciprocity, mimicry and positive interaction displays in HRI, has been linked with user engagement, positive emotional reactions and willingness to engage with social robots (Borghi *et al.*, 2023) . Despite considerable evidence for relations between these relational outcomes and positive attitudinal dispositions within the study of social psychology (Sprecher *et al.*, 2013), there is no empirical study modelling the relationship between rapport and attitude toward social robots. This critical path has not been included in the HRI TAM studies (Borghi *et al.*, 2023). This is especially important in the context of educational HRI in which a relationship between students and social robots has, in fact, already been demonstrated to affect education-specific outcomes like student engagement and learning. Given that rapport elicits positive feelings and willingness to interact with social robots, and that such relational consequences have been shown to influence attitudinal dispositions in interpersonal interactions (Sprecher *et al.*, 2013), it could be anticipated that students who develop rapport with the social robot will have favourable attitudes toward it. Thus:

H3. Rapport with social robots positively influences users' attitudes towards robots.

2.5 Attitude and behavioural intention

Within the TAM framework, attitude toward using the technology is an antecedent to behavioural intention. The attitude–behavioural intention relationship has been tested and supported using TAM and its extensions in the context of social robot adoption in hospitality and tourism, healthcare (Borges-Tiago *et al.*, 2026) . The findings consistently support that users with a more favourable evaluative orientation towards social robots would exhibit greater adoption intention. In the education field, students' positive attitude towards emerging technologies has consistently appeared as a predictor of greater behavioural intention to adopt the same (Pillai *et al.*, 2024) . However, only a few studies have investigated the relationship between user attitudes and behavioural intention toward specific categories of social robots, such as chatbots (Polyportis and Pahos, 2025) . Drawing on these findings, higher education students who hold positive attitudes toward social robots are more likely to form stronger behavioural intentions to use them as pedagogical agents. On this basis, we posit the following hypothesis:

H4. Attitudes towards social robots positively influence their behavioural intentions towards social robots.

2.6 The moderating role of motivations

Social robot users in educational contexts do not have a homogenous profile and may vary in their approaches toward social robots, which has important implications for how attitudinal evaluations translate into behavioural intentions. One such approach is motivation, defined as

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pleasure and enjoyment derived from interacting with a technology (Venkatesh *et al.*, 2012) . In the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), introduced by Venkatesh *et al.* (2012), motivation is an additional construct which, once again, has the same but often even greater effect on behavioural intention than performance expectancy. Likewise, motivated consumers are likely to react in a stronger manner to their subjective, enriching evaluation of a technology, because the anticipation of pleasure increases the motivational strength of an affirmative disposition, thus easing behavioural outcomes. Conversely, users with low motivation may have true positive attitudes towards a social robot, but may remain behaviourally uncommitted. This can be attributed to the absence of enjoyment expected from interacting with social robots that weakens the relationship between attitude and behavioural intention (Donnermann *et al.*, 2022). In educational settings, the intrinsic motivation to learn and utilize the social robot encourages behavioural commitment. Evidence for this phenomenon indicates that individuals with an expectation of enjoying the social robot interaction are more likely to convert their positive social robot attitudes into intentions to use it as a pedagogical agent. Thus, motivation does not act as an independent predictor of intention, but rather as a boundary condition regarding the relationship between attitude and behavioural intention. Thus:

H5. Motivation has a moderating effect on the relationship between attitudes and behavioural intentions towards social robots.

2.7 The moderating role of empathy

Social robot users in educational settings differ in their dispositional capacity for empathy. According to Davis (1983), empathy is the ability to adopt another person's perspective and share in their emotional experience. It can be understood as a personality trait and involves both cognitive components such as perspective taking and affective components such as empathic concern. Empathy as an individual difference variable has been included in other HRI acceptance research models, yet has never been studied as a moderator of the attitude–intention relationship. This moderator role may be especially critical to educational HRI, where a student's sympathizing disposition could be a key factor for accepting a robot as a meaningful teacher figure (Donnermann *et al.*, 2022). Given that empathic users have a tendency to attribute intentions and social meanings to other agents, including anthropomorphic agents, such as social robots, this may have implications on how positive attitudes towards social robots are translated into behavioural intentions towards them. Because high in empathy users tend to see social robots more as social interaction partners than as functional objects, the meaning of a positive attitude is more likely to be translated into a behavioural intention. Conversely, for users with low empathic tendencies who are unlikely to attribute any social meaning to the robot agent, a positive attitude towards the robot does not lead to a stronger intention to perform the behaviour. On these grounds, we hypothesize that:

H6. Empathy has a moderating effect on the relationship between attitudes and behavioural intentions towards social robots.

2.8 The moderating role of risk aversion

Another difference between the users of social robots is linked to generalized uncertainty and risk orientation, a personality trait that has been discussed in technology acceptance behaviour research. Users are risk averse when they avoid risks and prefer a lower risk alternative even if it is expected to yield a smaller benefit (Belanche *et al.*, 2020). Applied to technology acceptance, risk averse users are more sensitive towards uncertain features of an innovation. Indeed, uncertainty surrounding a technology when it is perceived to be high has often been linked to resistance to the adoption of a broad range of new technologies (Kim and Kim, 2021). It is worth noting, however, that risk aversion does not always make it impossible for users to

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form positive attitudes towards technology, as demonstrated in the case of a low-stakes, explorative educational experience. Instead, the suppression is based on a motivational gap between evaluation and intention; in particular, even positive attitudinal dispositions may not translate into strong intentions to behave. This can be attributed to the fact that depending on an autonomous, unpredictable agent entails an associated behavioural cost (Renn and Benighaus, 2013). The suppression effect has been found in related contexts, including AI assistants and robot journalists. In this context, risk aversion and uncertainty avoidance systematically weaken the attitude intention link, even when the attitudinal dispositions are positive (Kim and Kim, 2021). While risk aversion is identified as moderator in the relationship between human-likeness and use intention (Belanche *et al*., 2020), its potential moderating impact on the attitude-intention relationship has not been investigated in the context of social robot acceptance. Higher education represents a rather novel application domain for social robots as a type of autonomous agent. As their behaviour is rather unpredictable, it may be difficult for risk-averse students to turn positive evaluative stances into intentions to use robots (Donnermann *et al*., 2022). Therefore:

H7. Risk aversion has a moderating effect on the relationship between attitudes and behavioural intentions towards social robots.

2.9 The moderating role of technology readiness

Users of social robots at educational institutions differ from users of other sectors, such as retail, with regard to their motivational orientations, personality traits, and their generalized psychological preparedness to embrace new technologies, measured with the Technology Readiness Index (TRI) (Parasuraman, 2000; Parasuraman and Colby, 2015). TRI is a measure of technology readiness that was originally proposed by Parasuraman (2000) and modified by Parasuraman and Colby (2015) and pertains to the individual's tendency to utilize technology in their daily lives. The four dimensions are oppositely valenced. Optimism and innovativeness are the facilitators that predispose technology adoption. Discomfort and insecurity are associated with technology resistance. A meta-analysis of 193 independent samples by Blut and Wang (2020) found that technology readiness is a two-dimensional construct consisting of motivators (optimism and innovativeness) and inhibitors (discomfort and insecurity) with opposing effects on technology acceptance outcomes. Although the technology readiness variable has been extensively researched as a precursor of perceived usefulness, perceived ease of use and behavioural intention (Blut and Wang, 2020), there is a lack of systematic studies on the moderating effect of technology readiness on the attitude–intention relationship, especially in education and social robots.

Both optimism and innovativeness are likewise positively valenced dispositions with a behavioural element towards new technology that increase users' motivation to act in line with their evaluative states (Parasuraman, 2000; Blut and Wang, 2020). Optimistic users see new technology as a means for bringing control, flexibility and efficiency into their lives, whereas innovative users are looking for new technology and want to be the very first to use it. In educational settings, behavioural intentions towards technology are stronger for students who are more dispositional optimists and innovators, both of which are positively related to perceived usefulness, perceived ease of use and the attitude-intention gap (Blut and Wang, 2020). That said, a technology-disposed student who is optimistic and creative is more likely to have a strong intention to use social robots as pedagogical assistants if the disposition is accompanied with a positive attitude towards the robots because of the reduction in the psychological friction between attitude and intention. Hence:

H8a. Technology readiness motivators (optimism and innovativeness) have a moderating effect on the relationship between attitudes and behavioural intentions towards social robots.

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Discomfort and insecurity are inhibitors reflecting psychological resistance that structurally decouples attitudinal evaluation from intended behaviour (Parasuraman, 2000). Discomfort reflects a perceived lack of control over technology and a feeling of being overwhelmed by its complexity, whereas insecurity reflects a generalized distrust of technological systems and anxiety regarding their reliability and safety (Parasuraman, 2000; Blut and Wang, 2020). These dispositions are unlikely to inhibit the formation of a positive attitude toward a social robot. In low-stakes interactions, such as a robot-hosted educational experience without an act of commitment to the social robot, a mismatch occurs between the positive attitude toward a social robot and the discomfort and insecurity of acting toward an autonomous and unknown entity (Blut and Wang, 2020). This results in a systematic weakening of the attitude-intention link;. the attitude is still present, but the intention to act is inhibited by the discomfort and insecurity that accompanies it. Thus:

H8b. Technology readiness inhibitors (discomfort and insecurity) have a moderating effect on the relationship between attitudes and behavioural intentions towards social robots.

3. Methodology

3.1 Research design

To test the validity of our conceptual framework and research hypotheses, we followed a positivistic deductive approach and conducted a quantitative study using a structured questionnaire.

3.2 Sampling

In this survey, a two-stage cluster sampling method was used. In the first stage of sampling, 6 out of the 25 public universities in Greece were randomly selected from a complete list of all public universities using simple random sampling without replacement. As for the second phase of the study, a margin of error of 2% with a confidence level of 95% produced a minimum sample size of 641 (Chauvet and Vallée, 2020). Ultimately, the number of students participating in the study from each university was 150, bringing the final sample size to $N = 900$ students. The students who participated in the study were in their third and fourth years of study, as they were the ones eligible to apply for a graduate program in the near future.

Participant recruitment was conducted via the department secretariats at each university. Following an official email sent by the researchers to the department secretariats and user support departments on 20 May 2025, the secretariats forwarded the questionnaire link to eligible students enrolled in their third year or above. Participation was voluntary, anonymous and with no incentives offered. Data collection lasted seven months, from 20 May 2025 to 20 November 2025, and was concluded after it had been verified that at least 150 students from each of the six universities had answered the questionnaire. Based on official data from the Hellenic Authority for Higher Education (HAHE), the estimated eligible student population across the six participating universities was approximately 42,000, yielding an estimated macro-level response rate of approximately 2.14%. The achieved sample of $N = 900$ substantially exceeds the minimum required sample size of 641 students calculated using Cochran's (1977) formula at a 95% confidence level and 4% margin of error, ensuring the statistical adequacy of the findings. Finally, ethical approval for the study was granted by the Ethics and Deontology Committee of the University of West Attica (UNIWA) on 19 May 2025, prior to data collection.

3.3 Participants

The sample consisted of $N = 900$ university students from six public Greek universities, of whom 54.30% were female and 45.70% were male. Most of the participants were aged

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18–24 years (67.80%), 26.80% were aged 25–34 years and 5.40% of the sample were aged 35 years and above. The majority of respondents were enrolled in Business and Economics (38.20%), followed by Social Sciences, Engineering and Technology, Health Sciences and other fields (24.10%, 18.70%, 11.40% and 7.60% respectively). Regarding year of studies, 75. 90% were in their fourth year of their study program, followed by 17.20% were in their third year and 6.90% were in their fifth year. Participants' preferred study mode was in-person study (70.60%), followed by hybrid study mode (15.40%), and distance education (14.00%).

3.4 Materials

Before completing the scale items, all participants watched a 57-s standardised video depicting hypothetical scenarios in which social robots functioned as teaching assistants in postgraduate educational settings. The video received 1,400 views compared to 900 participants completing the study Since the questionnaire was constructed in such a way that the scale items were not accessible until after viewing the video, it can be confirmed that all participants had viewed the stimulus material. As social robots are not yet applied in Greek higher education settings, the video was designed to provide the participants with a common reference framework to form a shared expectation of the social robot's role in higher education settings. Thus, trust, satisfaction and rapport were assessed as anticipated responses in accordance with participants' expectation of what an interaction with such a robot would involve, rather than their evaluation of prior experience with it. This approach is in line with that in the TAM literature, which has used perceived and anticipated constructs in the absence of actual technology experience (Davis, 1989; Venkatesh *et al.*, 2003), as well as in other HRI studies with video stimuli to assess evaluative responses to social robots (Chuah and Yu, 2021; Yam *et al.*, 2021).

The operationalisation of rapport as an anticipated construct is methodologically consistent with the development of the Rapport-Expectation with a Robot Scale (Nomura and Kanda, 2016), which was developed and initially validated using video stimuli in which the participants were not actually interacting with the robot, thereby demonstrating that anticipated rapport with social robots is a meaningful and quantifiable construct that exists before actual HRI takes place. Similarly, the operationalisation of satisfaction as an anticipated construct is grounded in Oliver's (1999) expectancy-disconfirmation model, which posits that satisfaction is rooted in pre-interaction expectations, making it a meaningful construct to assess prior to actual interaction.

3.5 Measures

All constructs were measured using their respective seven-point Likert scales. For that purpose trust was measured with the four-item scale by Longoni *et al*. (2019) (e.g. I believe that the social robot would be trustworthy). Satisfaction was measured with the three-item scale of Bhattacherjee *et al*. (2001) (e.g. Using social robots would make me very pleased). Rapport was measured with the three-item scale of Gremler and Gwinner (2000) (e.g. I would look forward to seeing this social robot when attending classes at the university). Attitude and behavioural intention were measured with the two-item UTAUT scales of Venkatesh *et al*. (2003) (e.g. Using social robots in higher education would be a good idea/I intend to use social robots in higher education in the next 24 months). Furthermore, motivation (e.g. The use of social robots in higher education would stimulate my curiosity), empathy (e.g. When someone else feels excited about social robots, I tend to feel excited too), risk aversion (e.g. When I think about using social robots, I consider it safer to rely on technology I am already familiar with) and technology readiness (e.g. In general, I am among the first in my circle of friends to acquire new technology when it appears) were measured with the established scales of Moon and Kim (2001), Hong *et al*. (2017), Escalas and Stern (2003), Raju (1980) and the TRI 2.0 scale (Parasuraman and Colby, 2015), respectively. The researchers received formal approval from the original authors to use the tool, as the TRI 2.0 scale may only be used with the authors' prior consent.

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3.6 Data analysis

The proposed model was tested using the Structural Equation Modelling (SEM) in AMOS 29. Finally, to take into account possible nesting of the students in one of six universities, university dummy variables were included as covariates in the above structural model and their covariances were specified. This provided a means of controlling for the systematic variance associated with university membership. Following this procedure, all structural paths remained statistically significant and model fit indices were maintained at acceptable levels ($\chi^2/df = 2.623$, $CFI = 0.976$, $TLI = 0.971$, $RMSEA = 0.042$), providing evidence that the proposed relationships are robust to university-level clustering effects. Subsequently, moderated regression analyses were further conducted to investigate the moderation effects of motivation, empathy, risk aversion and technology readiness on the relationship between attitude and behavioural intention.

4. Data analysis and results

4.1 Scale validity and reliability

Confirmatory factor analysis was performed for all the scales and, later, the Average Variance Extracted (AVE), Composite Reliability (CR) coefficient and Cronbach a coefficient were calculated. Table 1 shows the results of these analyses. All the scales proved to be valid and reliable (French *et al.*, 2024), and the resulting data for each of the scales were then subsequently aggregated with the arithmetic mean into a single score. The normal distribution property of the scales was tested by checking skewness and kurtosis. It was found that the measures were approximately normally distributed. The skewness and kurtosis of the item scales and their descriptive statistics are shown in Table 1. Table 2 presents the correlations among the study constructs. All correlations were below 0.85, indicating no multicollinearity concerns.

Table 1. Descriptive statistics, validity and reliability

Constructs	M	SD	Skewness	Kurtosis	CR	Cronbach's a	AVE
Trust	4.971	1.197	−0.024	−0.851	0.932	0.913	0.725
Satisfaction	4.297	1.129	0.27	−0.235	0.882	0.881	0.712
Rapport	4.431	1.139	0.177	−0.222	0.821	0.814	0.611
Attitude	4.024	0.922	0.026	−0.108	0.819	0.852	0.590
Behavioural intention	3.949	0.867	−0.058	−0.017	0.817	0.810	0.587
Motivation	4.578	1.271	−0.675	0.315	0.832	0.828	0.603
Empathy	2.091	4.373	−0.367	−1.153	0.902	0.901	0.524
Risk aversion	4.565	1.313	−0.5	0.774	0.952	0.951	0.946
Technology readiness-optimism	5.026	1.101	−0.95	1.42	0.937	0.931	0.585
Technology readiness-innovativeness	4.456	1.221	−0.409	0.707	0.957	0.955	0.585
Technology readiness-discomfort	4.11	1.981	−0.064	−1.006	0.993	0.990	0.560
Technology readiness-insecurity	4.169	1.577	−0.072	−0.295	0.979	0.979	0.564

Table 2. Correlation matrix

	1	2	3	4	5
Trust	–				
Satisfaction	0.418	–			
Rapport	0.456	0.514	–		
Attitude	0.390	0.355	0.416	–	
Behavioural Intention	0.298	0.307	0.308	0.600	–

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Finally, to check for common method variance, Harman's single-factor test was performed, which revealed that the items from the different scales did not considerably load onto the same single factor ($p < 0.001$). Hence, common method variance did not constitute an important threat to the construct validity of the measurement (Podsakoff *et al*., 2003).

4.2 Hypothesis testing

SEM using AMOS 29 software was used to test the hypothesized conceptual framework. The measurement model and the path model were combined in one single model to test the validity. From the results in Table 3, the hypothesized model had a good fit ($\chi^2/df = 2.623$, $p < 0.001$, $CFI = 0.976$, $TLI = 0.971$ and $RMSEA = 0.042$). All fit indices achieved the recommended levels ($CFI > 0.95$, $TLI > 0.90$ and $RMSEA < 0.08$), indicating that the hypothesized relationships could be incorporated in a single model with an acceptable fit. Consequently, all path coefficients were important as expected. Trust ($\beta = 0.092$, $t = 3.291$, $p < 0.001$), satisfaction ($\beta = 0.067$, $t = 2.187$, $p < 0.05$) and rapport ($\beta = 0.118$, $t = 4.003$, $p < 0.001$) had a significant and positive effect on attitude towards social robots, collectively explaining 79.60% of the variance in attitude (*Adjusted* $R^2 = 0.714$). Hypotheses H1, H2 and H3 are therefore accepted. Finally, attitude was found to positively and significantly influence behavioural intention to use social robots ($\beta = 0.392$, $t = 10.679$, $p < 0.001$), explaining 73.40% of the variance in behavioural intention (Adjusted $R^2 = 0.702$) allowing us to accept H4.

4.3 Moderating effect of motivations

To test the validity of H5, which posits that user motivation moderates the relationship between attitude towards social robots and behavioural intention to use them, a moderated regression analysis was conducted with mean-centred variables to minimize multicollinearity. The regression model was constructed with behavioural intention as the dependent variable and attitude towards social robots, motivation, and their interaction term as independent variables (*Adjusted* $R^2 = 0.618$). VIF values were below 1.01, confirming the absence of multicollinearity. The results of the analysis (Table 4) indicate that behavioural intention is positively and significantly influenced by attitude ($\beta = 0.318$, $t = 12.339$, $p < 0.001$). However, motivation alone was not found to exert a significant direct effect on behavioural intention ($\beta = 0.015$, $t = 0.581$, $p > 0.05$). Critically, the moderating effect was found to be positive and significant ($\beta = 0.530$, $t = 20.59$, $p < 0.001$), providing evidence that motivation strengthens the relationship between attitude and behavioural intention. It is therefore reasonable to conclude that motivation has a positive moderating effect. That said, the higher the user's motivation, the stronger the positive relationship between attitude towards social robots and the intention to use them. H5 is therefore accepted.

4.4 Moderating effect of empathy

Hypothesis H6 was also tested by moderated regression analysis with behavioural intention as the dependent variable and attitude, empathy, and interaction as the independent variables (*Adjusted* $R^2 = 0.692$). VIF values were below 1.01, confirming the absence of multicollinearity. Unlike motivation, empathy was found to exert a significant direct effect

Table 3. Regression weights for the path model

	Estimate	SE	*T*	Adjusted R^2
Trust → Attitude	0.092	0.015	3.291**	
Satisfaction → Attitude	0.067	0.017	2.187*	
Rapport → Attitude	0.118	0.032	4.003**	0.714
Attitude → Behavioural intention	0.392	0.025	10.679**	0.702

Note(s): ** Significant at the 0.01 level; *Significant at the 0.05 level

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Table 4. Moderating effects

Hypothesis	Dependent variable	Independent variables	Standardized coefficients	*t*	Sig	Adjusted R^2
H5	Behavioural Intention	Attitude	0.318	12.339	<0.001	0.618
		Motivation	0.015	0.581	>0.05	
		Attitude × Motivation	0.530	20,590	<0.001	
H6	Behavioural Intention	Attitude	0.210	12.375	<0.001	0.692
		Empathy	0.088	5.303	<0.001	
		Attitude × Empathy	0.796	14,758	<0.001	
H7	Behavioural Intention	Attitude	0.369	14.578	<0.001	0.765
		Risk Aversion	0.113	6.758	<0.001	
		Attitude × Risk Aversion	−0.777	−21,256	<0.001	
H8a	Behavioural Intention	Attitude	0.311	14.315	<0.001	0.708
		Optimism	−0.110	−0.500	>0.05	
		Attitude × Optimism	0.664	12,134	<0.001	
H8a	Behavioural Intention	Attitude	0.360	13.544	<0.001	0.725
		Innovativeness	0.378	12.225	<0.001	
		Attitude × Innovativeness	0.165	5,325	<0.001	
H8b	Behavioural Intention	Attitude	0.356	12.659	<0.001	0.601
		Discomfort	−0.235	−7.518	<0.001	
		Attitude × Discomfort	−0.239	−7,650	<0.001	
H8b	Behavioural Intention	Attitude	0.363	13.249	<0.001	0.720
		Insecurity	−0.240	−7.582	<0.001	
		Attitude × Insecurity	−0.271	−8,571	<0.001	

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on behavioural intention ($\beta = 0.088$, $t = 5.303$, $p < 0.001$), in addition to attitude ($\beta = 0.210$, $t = 12.375$, $p < 0.001$). The moderating effect was positive and significant ($\beta = 0.796$, $t = 14.758$, $p < 0.001$), indicating that empathy strengthens the attitude–behavioural intention relationship. That means that the effect of attitude towards social robots on the intention to use social robots is stronger. Therefore, H6 is accepted.

4.5 Moderating effect of risk aversion

H7 was tested with a moderated regression analysis by taking the behavioural intention as the dependent variable and the attitude, risk aversion and interaction term as independent variables (*Adjusted* $R^2 = 0.765$).VIF values were below 1.01, confirming the absence of multicollinearity. As expected, risk aversion was found to influence intention positively and significantly ($\beta = 0.113$, $t = 6.758$, $p < 0.001$) in addition to the effect of the attitude ($\beta = 0.369$, $t = 14.578$, $p < 0.001$). The interaction term was negative and important ($\beta = -0.777$, $t = -21.256$, $p < 0.001$), indicating that the relationship between attitude and behavioural intention was negatively affected by the level of risk aversion. More specifically, the higher the level of dispositional risk aversion of the user, the less positive the impact of attitude on the intention to use social robots. H7 is therefore accepted.

4.6 Moderating effect of technology readiness

For H8a, two separate moderated regression analyses, were conducted for optimism and innovativeness. For optimism (*Adjusted* $R^2 = 0.708$) attitude ($\beta = 0.311$, $t = 14.315$, $p < 0.001$) was a significant predictor of behavioural intention, whereas the effect of optimism was non-significant ($\beta = -0.110$, $t = -0.500$, $p > 0.05$). Likewise, the moderating effect was significant ($\beta = 0.664$, $t = 12.134$, $p < 0.001$). In the PLS path model for innovativeness (*Adjusted* $R^2 = 0.725$), the relationship between attitude and behavioural intention was significant ($\beta = 0.360$, $t = 13.544$, $p < 0.001$) and the direct effect of innovativeness was also significant ($\beta = 0.378$, $t = 12.225$, $p < 0.001$). The moderating effect ($\beta = 0.165$, $t = 5.325$, $p < 0.001$) was found to be positive and significant, indicating both motivator dimensions augmented the positive influence of attitude on intention. Therefore, H8a is accepted.

To test H8b, moderated regression analyses were performed for discomfort. Attitude was confirmed as a significant positive predictor for behavioural intention ($\beta = 0.356$, $t = 12.659$, $p < 0.001$) and discomfort had a significant negative direct effect ($\beta = -0.235$, $t = -7.518$, $p < 0.001$) and interaction effect (*Adjusted* $R^2 = 0.601$) ($\beta = -0.239$, $t = -7.650$, $p < 0.001$). For insecurity, again, attitude was an important predictor of intention (*Adjusted* $R^2 = 0.720$) ($\beta = 0.363$, $t = 13.249$, $p < 0.001$). Additionally, insecurity had an important negative direct effect ($\beta = -0.240$, $t = -7.582$, $p < 0.001$) and a significant negative interaction effect ($\beta = -0.271$, $t = -8.571$, $p < 0.001$). VIF values were below 1.01, confirming the absence of multicollinearity. Consequently, both the structural and the contextual inhibitor dimension, attenuate the positive influence of attitude on intention. Thus, H8b is accepted.

5. Discussion

5.1 Theoretical contributions

This study examines the impact of trust, satisfaction and rapport on university students' attitudes and behavioural intention toward social robots, making theoretical contributions to the extended TAM. In addition to TAM and HRI research, the present research contributes theoretically to corporate communication research by operationalizing trust, satisfaction and rapport as the basic dimensions of quality of stakeholder relationship (SRQ) according to the Relationship Management Theory (Ledingham and Bruning, 2000) in the context of AI-mediated communication and the institution. When a university employs a social robot to assist as a teaching assistant, the robot functions as a represented institutional communication agent in mediating the institution-student relationship. Thus, students' trust, satisfaction and

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rapport with the robot can affect the quality of the relationship between the educational institution and its stakeholders, with implications for both student engagement and institutional reputation (Plaisance, 2023;Cornelissen, 2020).

First, the positive and statistically significant effect of trust on attitude (H1) extends the work of Horng *et al*. (2025) and Della Corte *et al*. (2023) to an educational HRI context by showing that trust has an earlier attitudinal effect on the acceptance process than the preceding studies (Gao *et al*., 2025). This finding suggests that trust serves an even earlier, attitudinally formative role in the acceptance process than previously established. This finding is consistent with the broader literature on trust in service encounters, which suggests that trust shapes evaluative orientations prior to behavioural commitment (Gursoy *et al*., 2023). In terms of educational HRI, this implies that social robots perceived as trustworthy and socially credible are more likely to elicit positive student attitudes. Lastly, in terms of communication, these results suggest that the robot's communicative behaviour (i.e. in terms of consistency, responsiveness and social appropriateness) functions as a trust signal that shapes student attitudes prior to behavioural commitment. Both educators and institutional leaders responsible for robot deployment should therefore focus not only on functional performance but also on the relational aspects of robot-mediated communication (Della Corte *et al*., 2023; Donnermann *et al*., 2022).

Second, the positive and significant effect of satisfaction on attitude (H2) extends the use of satisfaction as a direct antecedent of attitude as a new causal path in TAM, in contrast to the use of satisfaction and attitude as co-occurring consequences of robot interaction (Zhang *et al*., 2024; Oliver, 1999). This suggests that where students perceive their experience with a social robot as matching or exceeding their prior expectations, they are more likely to develop positive evaluative orientations towards the technology. Institutional communication efforts that offer students accurate and realistic information about social robots prior to their deployment are therefore likely to generate satisfying first encounters, which in turn supports the development of positive attitudes and sustained engagement with social robots as pedagogical agents (Oliver, 1999; Chugh *et al*., 2023).

Third, the role of rapport as the most important relational driver of attitude (H3) extends the sRAM model (Borghi *et al*., 2023) by confirming that rapport is not only a coordinative construct, but also an antecedent of attitude formation. This finding also reflects the literature on interpersonal communication where rapport has been shown to be an important mechanism driving relational closeness and relational evaluation (Gremler and Gwinner, 2000; Sprecher *et al*., 2013). In educational settings, this suggests that in addition to their physical design, social robots' communicative design, in terms of their attentiveness, reciprocity, and positive displays of interaction, is critical for student acceptance. From a practitioner perspective, this suggests that robot-mediated communication should prioritize relational rather than informational efficiency, by deploying robots that function as responsive communication partners, thereby establishing the attitudinal foundations necessary for sustained use.

Fourth, the attitude–behavioural intention link was confirmed (H4), thus replicating the original TAM hypothesis (Davis, 1989) and recent work in the educational technology field (Pillai *et al*., 2024). The finding that attitude is an important mediator between belief and intention in a novel context of social robots as pedagogical agents adds to the literature showing attitude as a key mediator across different technological settings (Kim *et al*., 2009; Pillai *et al*., 2024; Borges-Tiago *et al*., 2026). From a communicative standpoint, the finding suggests that positive institutional communication about social robots, which builds trust, manages expectations and fosters a sense of relational connection, is not merely a reputational concern but a direct driver of student behavioural engagement. In other words, how institutions communicate about and frame the introduction of social robots may determine how students feel about robots and whether they intend to use them.

Finally, all of the hypotheses related to the moderating effects were confirmed. Motivation (H5), empathy (H6) and technology readiness motivators (H8a) positively moderated the attitude–intention relationship, while risk aversion (H7) and technology readiness inhibitors

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(H8b) negatively moderated this relationship, suggesting that the attitude-intention relationship is somewhat flexible. Our study adds to current literature by providing evidence on dispositional boundary conditions of social robot acceptance in university students. These findings suggest that the attitude-intention relationship is not necessarily uniform for all students but is systematically moderated by certain dispositional traits that extend existing research on technology acceptance boundary conditions (Blut and Wang, 2020; Venkatesh *et al.*, 2012) and extends this research to the emerging field of social robot acceptance in higher education contexts.

Furthermore, in communicative terms, implications for educators and for educational institutions with regard to the introduction of social robots to students are that a one-size-fits-all approach is not likely to be effective given the diversity of student dispositions identified in this study. Specifically, institutions should use a communication strategy that matches students' dispositions. For students who are risk averse, communication should stress the low-stakes, exploratory nature of robot interaction. For students with high empathic concern, the social and relational aspects of robots should be highlighted. For students who are less intrinsically motivated to interact with robots, the hedonic and novelty aspects of robot interaction should be stressed. Finally, for students with high technological discomfort and insecurity, communication should emphasise that students would be familiarized with the robot before using it. The aforementioned segmentation strategies are in line with principles of strategic communication management such as audience segmentation and tailored communication approaches (Cornelissen, 2020). From an internal communication and change management perspective, the above segmentation strategies can be explained as part of a strategic institutional change management programme, designed and implemented by communication managers, to govern the introduction of robot-mediated communication as a strategic institutional decision that shapes the institution–student relationship quality (Ledingham and Bruning, 2000; Plaisance, 2023).

5.2 Managerial implications

The results have important implications for educational policymakers and institutional leaders.

From a corporate communication perspective, the use of social robots in higher education is a strategic institutional communication decision (Buhmann *et al.*, 2026; O'Neil and Vasquez, 2026). The adoption of this technology enables higher education institutions to manage their stakeholder relationships, institutional reputation, and their internal communication strategies. By deploying social robots as teaching assistants, social robots convey to their most important stakeholders, students, a willingness to offer innovative and personalised technology-enabled learning experiences in higher education (Lemon and Dhanesh, 2026). In this context, the present study identifies trust, satisfaction, and rapport as relational antecedents of student acceptance, which would support the design of deployment strategies to manage stakeholder relationships and protect institutional reputation (Skandali *et al.*, 2026).

Given the tight connection of trust, satisfaction and rapport with students' perceptions, it is important that institutions also consider the quality of the HRI when deciding whether or not to use social robots as teaching assistants. This includes the robots' ability to build trust through reliable behaviour, provide satisfaction through responsive interaction and achieve rapport through attentive, empathic and positive communication (Buhmann *et al.*, 2026; Lemon and Dhanesh, 2026).

Therefore, while it may not be possible for all students to adopt robots in the same way, institutions may be able to address the individual difference effects identified here by, for example, introducing students to robots in low-risk exploratory situations in order to alleviate the impact of risk aversion on use intention; making use of warm and social responsive robot characteristics to engage students with lower levels of empathy; incorporating gamification or humour into robots to inspire use among students with lower levels of intrinsic motivation and offering students opportunities to make themselves comfortable with robots before

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deployment to address technological discomfort and insecurity (Venkatesh *et al*., 2012; Blume *et al*., 2025). Rather than being the only internal communication and change management strategies, these should be viewed as part of communication activities planned by communication managers as part of an institutional communication program before and during robot deployment. Segmented communication to different student audiences, according to pre-deployment individual student dispositions, can help institutions to leverage stakeholder acceptance, relationship quality and institutional reputation (Ledingham and Bruning, 2000; Plaisance, 2023;Cornelissen, 2020).

5.3 Limitations and future research directions

Despite the contributions achieved here, there are some limitations that deserve to be mentioned and suggest promising paths for future research.

Because this research used a cross-sectional design, it does not allow for causality and the possibility to observe how attitudes and intentions towards social robots develop over time. Future studies with longitudinal designs are needed to test whether the identified antecedents for establishing a relationship with social robots (i.e. trust, satisfaction, rapport) can increase or decrease with repeated social robot interactions (Donnermann *et al*., 2022).

References

Agag, G., Shehawy, Y.M., Almoraish, A., Eid, R., Lababdi, H.C., Labben, T.G. and Abdo, S.S. (2024), "Understanding the relationship between marketing analytics, customer agility, and customer satisfaction: a longitudinal perspective", *Journal of Retailing and Consumer Services*, Vol. 77, 103663, doi: 10.1016/j.jretconser.2023.103663.

Alhmiedat, T., Marei, A.M., Messoudi, W., Albelwi, S., Bushnag, A., Bassfar, Z., Alnajjar, F. and Elfaki, A.O. (2023), "A SLAM-based localization and navigation system for social robots: the pepper robot case", *Machines*, Vol. 11 No. 2, p. 158, doi: 10.3390/machines11020158.

Belanche, D., Casaló, L.V., Flavián, C. and Schepers, J. (2020), "Service robot implementation: a theoretical framework and research agenda", *The Service Industries Journal*, Vol. 40 Nos 3-4, pp. 203-225, doi: 10.1080/02642069.2019.1672666.

Belpaeme, T., Vogt, P., Van den Berghe, R., Bergmann, K., Göksun, T., De Haas, M., Pandey, A.K., Kennedy, J., Küntay, A.C., Oudgenoeg-Paz, O., Papadopoulos, F., Schodde, T., Verhagen, J., Wallbridge, C.D., Willemsen, B., de Wit, J., Geçkin, V., Hoffmann, L., Kopp, S., Krahmer, E., Mamus, E., Montanier, J.M. and Oranç, C. (2018), "Guidelines for designing social robots as second language tutors", *International Journal of Social Robotics*, Vol. 10 No. 3, pp. 325-341, doi: 10.1007/s12369-018-0467-6.

Bhattacherjee, A. (2001), "Understanding information systems continuance: an expectation-confirmation model", *MIS Quarterly*, Vol. 25 No. 3, pp. 351-370, doi: 10.2307/3250921.

Blume, C., de Winter, J.C.F. and Moorlag, F. (2025), "Social robots: a meta-analysis of learning outcomes", *Frontiers in Robotics and AI*, Vol. 12, 1735198.

Blut, M. and Wang, C. (2020), "Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage", *Journal of the Academy of Marketing Science*, Vol. 48 No. 4, pp. 649-669, doi: 10.1007/s11747-019-00680-8.

Borges-Tiago, M.T., Tiago, F., Ataíde, R. and Cosme, C. (2026), "Technology or service experience? Exploring consumer intention behavior in RSA restaurants", *Psychology and Marketing*, Vol. 43 No. 1.

Borghi, M., Mariani, M.M., Perez-Vega, R. and Wirtz, J. (2023), "The impact of service robots on customer satisfaction online ratings: the moderating effects of rapport and contextual review factors", *Psychology and Marketing*, Vol. 40 No. 11, pp. 2355-2369, doi: 10.1002/mar.21903.

Buhmann, A., Zerfass, A., Laborde, A., Moreno, A., Romenti, S., Tench, R. and Siegel, C. (2026), "'We're right in the foothills': the adoption of artificial intelligence in corporate communication

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departments", *Corporate Communications: An International Journal*, pp. 1-21, doi: 10.1108/ccij-09-2025-0296.

Chauvet, G. and Vallée, A.A. (2020), "Inference for two-stage sampling designs", *Journal of the Royal Statistical Society Series B: Statistical Methodology*, Vol. 82 No. 3, pp. 797-815, doi: 10.1111/rssb.12368.

Chuah, S.H.W. and Yu, J. (2021), "The future of service: the power of emotion in human-robot interaction", *Journal of Retailing and Consumer Services*, Vol. 61, 102551, doi: 10.1016/j.jretconser.2021.102551.

Chugh, R., Turnbull, D., Cowling, M.A., Vanderburg, R. and Vanderburg, M.A. (2023), "Implementing educational technology in Higher Education Institutions: a review of technologies, stakeholder perceptions, frameworks and metrics", *Education and Information Technologies*, Vol. 28 No. 12, pp. 16403-16429, doi: 10.1007/s10639-023-11846-x.

Cochran, W.G. (1977), *Sampling Techniques*, 3rd ed., John Wiley & Sons, New York, NY, doi: 10.1002/bimj.19650070312.

Cornelissen, J. (2020), *Corporate Communication: A Guide to Theory and Practice*, 6th ed., SAGE Publications, London.

Davis, M.H. (1983), "Measuring individual differences in empathy: evidence for a multidimensional approach", *Journal of Personality and Social Psychology*, Vol. 44 No. 1, pp. 113-126, doi: 10.1037/0022-3514.44.1.113.

Davis, F.D. (1985), "A technology acceptance model for empirically testing new end-user information systems: theory and results", Doctoral dissertation, Massachusetts Institute of Technology.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340, doi: 10.2307/249008.

Della Corte, V., Sepe, F., Gursoy, D. and Prisco, A. (2023), "Role of trust in customer attitude and behaviour formation towards social service robots", *International Journal of Hospitality Management*, Vol. 114, 103587, doi: 10.1016/j.ijhm.2023.103587.

Donnermann, M., Schaper, P. and Lugrin, B. (2022), "Social robots in applied settings: a long-term study on adaptive robotic tutors in higher education", *Frontiers in Robotics and AI*, Vol. 9, 831633, doi: 10.3389/frobt.2022.831633.

Escalas, J.E. and Stern, B.B. (2003), "Sympathy and empathy: emotional responses to advertising dramas", *Journal of Consumer Research*, Vol. 29 No. 4, pp. 566-578, doi: 10.1086/346251.

French, R.C., Kennedy, D.P. and Krendl, A.C. (2024), "Establishing construct validity for dynamic measures of behavior using naturalistic study designs", *Behavior Research Methods*, Vol. 57 No. 1, p. 2, doi: 10.3758/s13428-024-02519-9.

Gao, Y., Chang, Y., Yang, T. and Yu, Z. (2025), "Consumer acceptance of social robots in domestic settings: a human-robot interaction perspective", *Journal of Retailing and Consumer Services*, Vol. 82, 104075, doi: 10.1016/j.jretconser.2024.104075.

Gremler, D.D. and Gwinner, K.P. (2000), "Customer-employee rapport in service relationships", *Journal of Service Research*, Vol. 3 No. 1, pp. 82-104, doi: 10.1177/109467050031006.

Guggemos, J., Seufert, S. and Sonderegger, S. (2020), "Humanoid robots in higher education: evaluating the acceptance of Pepper in the context of an academic writing course using the UTAUT", *British Journal of Educational Technology*, Vol. 51 No. 5, pp. 1864-1883, doi: 10.1111/bjet.13006.

Gursoy, D., Li, Y. and Song, H. (2023), "ChatGPT and the hospitality and tourism industry: an overview of current trends and future research directions", *Journal of Hospitality Marketing and Management*, Vol. 32 No. 5, pp. 579-592, doi: 10.2307/249008.

Hong, J.C., Lin, P.H. and Hsieh, P.C. (2017), "The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch", *Computers in Human Behavior*, Vol. 67, pp. 264-272, doi: 10.1016/j.chb.2016.11.001.

Horng, J.S., Wang, Y.C., Liu, C.H., Chou, S.F., Yu, T.Y., Huang, Y.C. and Hu, D.C. (2025), "Robot anthropomorphism at luxury hotels: a dual-congruity mechanism with luxury and task under

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anxiety", *Journal of Hospitality Marketing and Management*, Vol. 34 No. 2, pp. 204-233, doi: 10.1080/19368623.2024.2425673.

Hu, C., Li, F., Wang, S., Gao, Z., Pan, S. and Qing, M. (2025), "The role of artificial intelligence in enhancing personalized learning pathways and clinical training in dental education", *Cogent Education*, Vol. 12 No. 1, 2490425, doi: 10.1080/2331186x.2025.2490425.

Johannessen, L.E., Rasmussen, E.B. and Haldar, M. (2023), "Student at a distance: exploring the potential and prerequisites of using telepresence robots in schools", *Oxford Review of Education*, Vol. 49 No. 2, pp. 153-170, doi: 10.1080/03054985.2022.2034610.

Kim, D. and Kim, S. (2021), "A model for user acceptance of robot journalism: influence of positive disconfirmation and uncertainty avoidance", *Technological Forecasting and Social Change*, Vol. 163, 120448, doi: 10.1016/j.techfore.2020.120448.

Kim, Y.J., Chun, J.U. and Song, J. (2009), "Investigating the role of attitude in technology acceptance from an attitude strength perspective", *International Journal of Information Management*, Vol. 29 No. 1, pp. 67-77, doi: 10.1016/j.ijinfomgt.2008.01.011.

Ledingham, J.A. and Bruning, S.D. (2000), *Public Relations as Relationship Management: A Relational Approach to the Study and Practice of Public Relations*, Routledge.

Lemon, L.L. and Dhanesh, G.S. (2026), "Will I lose my creative edge?: Exploring how AI impacts internal communication and employee engagement", *Corporate Communications: An International Journal*, Vol. 31 No. 5, pp. 1-17, doi: 10.1108/ccij-11-2025-0355.

Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019), "Resistance to medical artificial intelligence", *Journal of Consumer Research*, Vol. 46 No. 4, pp. 629-650, doi: 10.1093/jcr/ucz013.

Mahr, D., Odekerken-Schröder, G. and Van Doorn, J. (2025), "Evolution of service robots in marketing: a relational framework and future research agenda", *Journal of Business Research*, Vol. 192, 115204, doi: 10.1016/j.jbusres.2025.115204.

Moon, J.W. and Kim, Y.G. (2001), "Extending the TAM for a World-Wide-Web context", *Information and Management*, Vol. 38 No. 4, pp. 217-230, doi: 10.1016/s0378-7206(00)00061-6.

Nertinger, S., Kirschner, R.J., Naceri, A. and Haddadin, S. (2024), "Acceptance of remote assistive robots with and without human-in-the-loop for healthcare applications", *International Journal of Social Robotics*, Vol. 16 No. 6, pp. 1131-1150, doi: 10.1007/s12369-022-00931-9.

Nomura, T. and Kanda, T. (2016), "Rapport–expectation with a robot scale", *International Journal of Social Robotics*, Vol. 8 No. 1, pp. 21-30, doi: 10.1007/s12369-015-0293-z.

O'Neil, J. and Vasquez, R.A. (2026), "The role and value of senior communicators in the AI era: ethical guardians, relationship champions, trainers, and strategic advisors", *Corporate Communications: An International Journal*, Vol. 31 No. 7, pp. 39-61, doi: 10.1108/ccij-11-2025-0374.

Oliver, R.L. (1999), "Whence consumer loyalty?", *Journal of Marketing*, Vol. 63, pp. 33-44, doi: 10.2307/1252099.

Parasuraman, A. (2000), "Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies", *Journal of Service Research*, Vol. 2 No. 4, pp. 307-320, doi: 10.1177/109467050024001.

Parasuraman, A. and Colby, C.L. (2015), "An updated and streamlined technology readiness index: TRI 2.0", *Journal of Service Research*, Vol. 18 No. 1, pp. 59-74, doi: 10.1177/1094670514539730.

Pillai, R., Sivathanu, B., Metri, B. and Kaushik, N. (2024), "Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education", *Information Technology and People*, Vol. 37 No. 1, pp. 328-355, doi: 10.1108/itp-02-2021-0152.

Plaisance, G. (2023), "Improving relationship quality with stakeholders to increase nonprofit organizations' impact: the mediating role of students' contributions", *Journal of Nonprofit and Public Sector Marketing*, Vol. 35 No. 5, pp. 521-552, doi: 10.1080/10495142.2022.2032531.

Downloaded from www.emerald.com/ccij/article-pdf/31/7/142/11913721/ccij-07-2026-0348en.pdf by Liverpool John Moores University user on 13 November 2026

Podsakoff, N.P., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 885 No. 879, pp. 10-1037, doi: 10.1037/0021-9010.88.5.879.

Polyportis, A. and Pahos, N. (2024), "Navigating the perils of artificial intelligence: a focused review on ChatGPT and responsible research and innovation", *Humanities and Social Sciences Communications*, Vol. 11 No. 1, p. 107, doi: 10.1057/s41599-023-02464-6.

Polyportis, A. and Pahos, N. (2025), "Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy", *Behaviour and Information Technology*, Vol. 44 No. 2, pp. 315-336, doi: 10.1080/0144929x.2024.2317364.

Premathilake, G.W., Li, H., Li, C., Liu, Y. and Han, S. (2025), "Understanding the effect of anthropomorphic features of humanoid social robots on user satisfaction: a stimulus-organism-response approach", *Industrial Management and Data Systems*, Vol. 125 No. 2, pp. 768-796, doi: 10.1108/imds-10-2023-0781.

Raju, P.S. (1980), "Optimum stimulation level: its relationship to personality, demographics, and exploratory behavior", *Journal of Consumer Research*, Vol. 7 No. 3, pp. 272-282, doi: 10.1086/208815.

Renn, O. and Benighaus, C. (2013), "Perception of technological risk: insights from research and lessons for risk communication and management", *Journal of Risk Research*, Vol. 16 Nos 3-4, pp. 293-313, doi: 10.1080/13669877.2012.729522.

Robaczewski, A., Bouchard, J., Bouchard, K. and Gaboury, S. (2021), "Socially assistive robots: the specific case of the NAO", *International Journal of Social Robotics*, Vol. 13 No. 4, pp. 795-831, doi: 10.1007/s12369-020-00664-7.

Said, H., Malek, J.A., Hamzah, M.I. and Hashim, R. (2023), "Perceived usefulness and perceived ease of use on re-patronage intention of humanoid service robots: cross-cultural comparison between Asian and non-Asian hotel customers", *Journal of Hospitality and Tourism Technology*, Vol. 14 No. 2, pp. 179-196.

Shiomi, M., Tamura, Y., Kimoto, M., Iio, T., Akahane-Yamada, R. and Shimohara, K. (2021), "Two is better than one: verification of the effect of praise from two robots on pre-school children's learning time", *Advanced Robotics*, Vol. 35 No. 19, pp. 1132-1144, doi: 10.1080/01691864.2021.1970019.

Skandali, D., Bayar, S.B., Ali, F. and Cobanoglu, C. (2026), "Artificial intimacy at work: how digital nomads build trust in generative AI companions and implications for remote corporate communication", *Corporate Communications: An International Journal*, Vol. 31 No. 1, pp. 54-70, doi: 10.1108/ccij-08-2025-0230.

Song, X., Gu, H., Ling, X., Ye, W., Li, X. and Zhu, Z. (2024), "Understanding trust and rapport in hotel service encounters: extending the service robot acceptance model", *Journal of Hospitality and Tourism Technology*, Vol. 15 No. 5, pp. 842-861, doi: 10.1108/jhtt-12-2023-0428.

Sprecher, S., Treger, S., Wondra, J.D., Hilaire, N. and Wallpe, K. (2013), "Taking turns: reciprocal self-disclosure promotes liking in initial interactions", *Journal of Experimental Social Psychology*, Vol. 49 No. 5, pp. 860-866, doi: 10.1016/j.jesp.2013.03.017.

Turner, A., Zillner, C., Rockenbauer, G. and Pletschko, T. (2026), "Success factors for the social inclusion and school belonging of children and adolescents with chronic Health conditions using telepresence robots", *European Journal of Inclusive Education (EJIE)*, Vol. 5 No. 1, pp. 1-18, doi: 10.7146/ejie.v5i1.150150.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478, doi: 10.2307/30036540.

Venkatesh, V., Thong, J.Y. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178, doi: 10.2307/41410412.

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Woo, H., LeTendre, G.K., Pham-Shouse, T. and Xiong, Y. (2021), "The use of social robots in classrooms: a review of field-based studies", *Educational Research Review*, Vol. 33, 100388, doi: 10.1016/j.edurev.2021.100388.

Yam, K.C., Bigman, Y.E., Tang, P.M., Ilies, R., De Cremer, D., Soh, H. and Gray, K. (2021), "Robots at work: people prefer—and forgive—service robots with perceived feelings", *Journal of Applied Psychology*, Vol. 106 No. 10, pp. 1557-1572, doi: 10.1037/apl0000834.

Zhang, W., Slade, E.L. and Pantano, E. (2024), "Humanlike service robots: a systematic literature review and research agenda", *Psychology and Marketing*, Vol. 41 No. 12, pp. 3157-3181, doi: 10.1002/mar.22099.

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