EAI Endorsed Transactions
on Tourism, Technology and Intelligence

Research Article EAI.EU

An Examination of Factors Shaping Students' Acceptance of Generative AI

Hang Le Nguyen Tue[1], Linh Tran-Thi-My[1*], Dieu Duong Thi Xuan[1]

[1] Duy Tan University, Danang, Vietnam

Abstract

Recognizing the proliferation of generative artificial intelligence (AI) technologies in facilitating student learning, this study seeks to explore the key drivers shaping students' intention to use this technology. Grounded in the Stimulus–Organism–Response (S–O–R) framework, we develop an integrative conceptual model and employ PLS-SEM to analyze data collected from 370 tourism students. The article reveals that peer and family influence exert a profound influence on the formation of usage-related expectations and trust. Meanwhile, anthropomorphism serves as an antecedent in shaping perceived usefulness and trust. Trust and perceived ease of use function as organism variables and significantly influence students' intention. Importantly, trust emerges as a key driver in forming students' intention to use generative AI. These findings provide implications for academic institutions in formulating AI adoption strategies to enhance teaching and learning practices.

Keywords: Generative AI; trust; usage-related expectations; education; tourism

Received on 16 January 2026, accepted on 03 March 2026, published on 09 March 2026

doi: 10.4108/eettti.11597

1. Introduction

Generative AI is a disruptive technology that utilizes multi-layered learning frameworks to create human-simulated material tailored to intricate requests [41]. This technology has garnered global attention, driving innovation in higher education while also presenting numerous challenges in this context [36]. Considering the rapid expansion of AI, exploring methods that help educators utilize AI-based applications to improve student academic outcomes is crucial [67]. With the ability to generate data-informed insights to adjust personalized training programs, generative AI platforms (e.g., ChatGPT, DeepSeek, and Gemini) enhance student participation, learning effectiveness, and knowledge construction through customized feedback, learning in digital mediated networks, and collaborative problem resolution [65]. For example, generative AI is reshaping the future of education, with ChatGPT playing a role in co-authoring and supporting the publication of research articles [36].

*Corresponding author. Email: trantmylinh5@duytan.edu.vn

Despite the proliferation of AI-driven pedagogical tools, research on students' academic performance and their behavioral intention to use AI for pedagogical purposes remains limited [10] [45], particularly with respect to tourism and hospitality students' attitudes and behaviors toward AI [63]. This leaves room for further investigation.

Generative AI has garnered widespread interest among academics, industry experts, and policy decision-makers from multiple perspectives, generating significant debate [18]. Trustworthiness in AI applications, such as Generative AI, directly affects the extent of student adoption and the effectiveness of AI use in learning [6]. Building trust in AI requires a thorough understanding of antecedents that predict individuals' behavior toward AI and the usage context. Trust truly forms only when users perceive the AI's reliability through appropriate signals; furthermore, human-related factors can be designed to enhance trust without necessarily improving AI performance [2]. However, trust in AI emerges as a critical concern for Private and institutional entities in the adoption of this technology [31] [57]. Users tend to evaluate trust in AI less favorably than trust in humans, partly because they tend to display negative attitudes toward AI-based translation algorithms, thereby opening avenues for further scholarly inquiry [13].

In marketing and psychology, anthropomorphism refers to how individuals perceive AI as possessing human-like traits. This perception plays a key role in understanding individuals' experiences with non-animated entities [9]. Anthropomorphism shapes human behavior toward AI [35]. Anthropomorphic AI chatbots have the potential to increase students' learning motivation [64]. Additionally, although trustworthiness is a primary predictor of individuals' interactions with and decisions regarding AI technologies, research in certain domains often lacks sufficient consideration of the role of trust in AI-enabled robots [16]. Anthropomorphism is categorized under "user-related" antecedents of trust in AI. The fewer people anthropomorphize entities, the less likely they are to trust an AI tool to perform its intended task, increasing AI resistance. Although the roles of human-like trust (e.g., anthropomorphism) and trust in AI have been acknowledged [16] [64], research exploring these factors and their interrelationship in shaping behavior toward AI remains scarce.

Given these points, we investigate the underlying antecedents shaping students' acceptance of generative AI in their learning journey. Furthermore, it examines the contributions of anthropomorphism and trust in the realm of AI use within academic settings. Accordingly, the following research questions (RQ) are proposed.

RQ1: *What potential drivers shape students' intention to use generative AI?*

RQ2: *To what extent do anthropomorphism and trust shape students' use of generative AI?*

The S–O–R diagram is adopted to explain students' behavior toward generative AI. To extend the theory and enhance its relevance to the educational context, anthropomorphism and trust are incorporated into the research model. Following the introduction, the paper proceeds with the literature review, research design, and empirical results. By filling a significant gap in the literature on the application of generative AI in education, this research offers several suggestions for policymakers and educators to explore the drivers behind students' intentions to use this technology.

2. Literature review

2.1. Generative AI in academic settings

AI can perform cognitive functions involving human cognition [30]. There are three main AI types: (1) weak AI concentrates exclusively on a discrete task, (2) general AI with human-like cognitive abilities can perform complex and varied tasks, and (3) super AI is expected to surpass human intelligence [43]. Advances in big data, cloud-based computing technologies, artificial neural network architectures, and algorithmic frameworks have laid the foundation for the emergence of AI, systems capable of simulating human intelligence in sensing, learning, and problem-solving [60]. The ubiquitous presence of AI has fostered global GDP by approximately 7% while displacing around 300 million knowledge-based jobs [22]. In the educational context, AI supports students' learning effectiveness by providing a tailored learning experience and content creation [42]. For example, generative AI (e.g., ChatGPT) has become increasingly popular in educational integration and has transformed learners' experiences [27].

AI can perform cognitive functions involving human cognition [30]. There are three main AI types: (1) weak AI concentrates exclusively on a discrete task, (2) general AI with human-like cognitive abilities can perform complex and varied tasks, and (3) super AI is expected to surpass human intelligence [43]. Advances in big data, cloud-based computing technologies, artificial neural network architectures, and algorithmic frameworks have laid the foundation for the emergence of AI, systems capable of simulating human intelligence in sensing, learning, and problem-solving [60]. The ubiquitous presence of AI has fostered global GDP by approximately 7% while displacing around 300 million knowledge-based jobs [22]. In the educational context, AI supports students' learning effectiveness by providing a tailored learning experience and content creation [42]. For example, generative AI (e.g., ChatGPT) has become increasingly popular in educational integration and has transformed learners' experiences [27].
Generative AI is classified as a specialized branch of AI designed to create text, visual content, and other types of output by utilizing probabilistic models trained across diverse domains [21.

2.2. The S-O-R Paradigm

Widely recognized paradigms governing technology, such as the Technology Acceptance Model (TAM), Task–Technology Fit (TTF), and the Unified Theory of Acceptance and Use of Technology (UTAUT), were initially engineered to explain non-humanlike technologies [24]. As such, they are limited in their ability to explain the complex interactions between AI and humans, particularly those involving emotional engagement and underlying psychological mechanisms [61]. Importantly, individuals' acceptance or rejection of AI represents a complex process shaped by external influences and user perceptions [24]. The S–O–R theory is a cognitive–behavioral framework that explains how stimuli (environmental attributes) shape responses (behavioral outcomes) through the organism, which encompasses individuals' perceptions and emotions [40]. Furthermore, this theory has been adopted in pedagogical research; for example, it has been used to comprehensively analyze the profound psychosocial toll of the pandemic on learners [47]. The S–O–R triadic model has been extended to various domains, allowing researchers to incorporate context-specific factors such as technological experience, advertising stimuli, website experience, and consumer behavior [28]. Thus, the framework is well-suited to this study on generative AI in pedagogical contexts.

Stimulus: Social norms and anthropomorphism. Stimulus denotes external environmental or socio-cognitive cues that trigger internal cognitive and affective states [32]. They act as part of the environment, and unexpected transformations in this setting can affect mental and affective stability, which in turn influences behavioral outcomes [17] [59]. Social norms refer to a set of criteria used to evaluate personal appraisals, which are influenced by the expectations of important referent groups around them that they should use novel technologies [55]. It is considered a source of external impact, shaping behavior directly [56]. Additionally, anthropomorphism is one of the social attributes of robots, which is reflected through three main aspects: perceived warmth, perceived competence, and perceived discomfort [60]. Students tend to anthropomorphize AI and feel more interested when interacting with it. Thus, depending on personal traits and initial expectations, anthropomorphism presents a double-edged sword for pedagogical outcomes. In educational contexts, anthropomorphizing technology can improve learning efficiency. When students perceive human-like traits in an AI tutor, they may achieve better learning outcomes [1]. Anthropomorphism helps us understand that when human-like cues are activated, users tend to perceive objects as more easily understood. This feature explains how travelers may feel more familiar and comfortable with a destination, while also encouraging them to behave more positively, adapt better, and reduce antisocial behaviors during their travels [34]. Anthropomorphism is associated with trust, performance expectancy, and effort expectancy, operating as the catalysts for students' adoption of generative AI (e.g., ChatGPT-driven pedagogical tools) [48]. Their tendency to anthropomorphize large language model chatbots (e.g., ChatGPT, Gemini) can be beneficial for education rather than a hindrance [51]. Thus, this study uses social norms and anthropomorphism as the "stimulus" in the psychological framework, influencing students' adoption of AI.

Organisms: Perceived technology attributes (usefulness, ease of use) and trust. The "organism" represents internal states, including emotional, cognitive, and physiological responses [40]. Perceived usefulness and perceived ease of use are two important drivers of the TAM, and they have been used to explain students' intention to use generative AI (e.g., ChatGPT) in tourism and hospitality education. Perceived usefulness reflects the subjective conviction of students that AI helps them complete tasks in education, and perceived ease of use reflects the prevalence of their belief that using AI requires minimal cognitive effort in their studies [14] [15] [55] [69]. Thanks to advanced AI algorithms (e.g., ChatGPT), students only need to input simple instructions related to tourism education, and the system handles the rest [69].

Trust serves as a fundamental cornerstone in shaping students' intention to use ChatGPT in tourism and hospitality education [68]. Trust serves as a conditioning antecedent in the proliferation of AI technologies, thereby fostering AI adoption [2]. To maintain a long-term user-technology interaction, it is imperative to understand users' perceptual and evaluative states, such as trustworthiness, during encounters with AI. Human-related factors should be integrated into AI development to ensure a positive user experience, continuous trust, and effective AI adoption [3].

Thus, we use perceived technology attributes (usefulness, ease of use) and trust as the "organism" in the psychological framework, influencing students' adoption of AI.

Stimuli directly shape organisms [40]. Social norms exert a significant influence on usage-related expectations of AI (e.g., usefulness, ease of use) [15] [16] [55]. Similarly, Confidence in technological systems is driven by contextual factors (e.g., social norms) [8]. Likewise, users' trust in social networking services is primarily shaped by social influence [46]. It is therefore hypothesized that:

H1: Social norms significantly impact perceived usefulness.

H2: Social norms significantly impact perceived ease of use.

H3: Social norms significantly impact trust in generative AI.

Anthropomorphism exerts a notable impact on usage-related expectations (e.g., usefulness; ease of use) [9] [60]. Alongside its role in enhancing a sense of social connectedness, anthropomorphism leads to increased perceived usefulness and favorable emotional reactions toward AI devices [7]. Furthermore, users' perceptions of anthropomorphic features in AI and emotions shape their trust [54]. This human-like trait enhances the social and task appeal of virtual assistants, thereby reinforcing users' cognitive and emotional trust in them [11]. Hence, we suggest the following hypotheses:

H4: Anthropomorphism significantly impacts perceived usefulness.

H5: Anthropomorphism significantly impacts perceived ease of use.

H6: Anthropomorphism significantly impact trust in generative AI.

Response: Intention to use generative AI. Response refers to behaviour that is shaped by the external environment through psychological and emotional factors [17]. Intentions are signals that indicate how a person attempts to perform an action or their belief in their willingness to carry out a given action [10]. Individuals' behavioural intentions are influenced by the dualistic nature of motivational drivers [52]. Indeed, positive learning confidence, intrinsic motivation, and extrinsic motivation influence learners' intentions, indicating that enhancing confidence and perceptions of the importance of using AI can strengthen students' learning intentions [62]. A person's intention to adopt a novel technology is directly motivated by performance expectancy and effort expectancy [50]. Furthermore, trust functions as a critical antecedent that influences individuals' behavioural intentions [53]. Thereby, we hypothesize:

H7: Perceived usefulness significantly impacts students' intention to use generative AI.

H8: Perceived ease of use significantly impacts students' intention to use generative AI.

H9: Trust in AI significantly impacts students' intention to use.

Given these points, we develop a conceptual framework (see Figure 1)

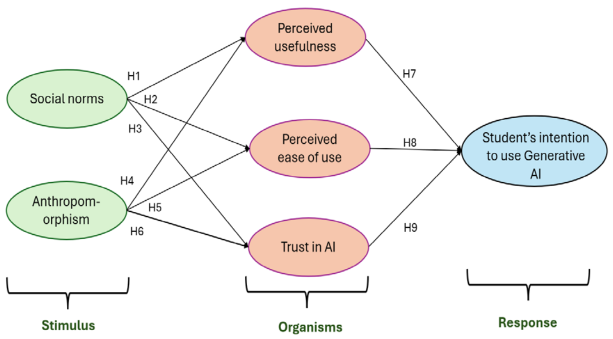

Figure 1. The hypothesized structural path

3. Methodology

3.1. Scale items

This study utilized 25 scale items from prior research on AI and technology to develop a questionnaire. Specifically, 4 scale items for anthropomorphism were adapted from [7] [11] [55]. Additionally, 4 scale items for perceived usefulness, 4 items for perceived ease of use, and 5 items for social influence were drawn from [15] [55]. Trust in AI (4 scale items) adapted from [33] and [66], while 4 scale items for intention to use generative AI were derived from [58]. All measurement items were assessed utilizing a seven-point Likert-type scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The items were reviewed and validated by two experts in tourism and education. A preliminary pilot study was performed with a sample of 100 tourism students to examine the quality of scale items and factors

3.2. Empirical data collection

The investigation was conducted in the Central region of Vietnam. Participants were students studying in the tourism and hospitality industry. The survey was conducted at Duy Tan University, which is the largest private university in the Central region and trains the largest proportion of tourism and hospitality students in this area. Moreover, students at this university come from various regions of Vietnam. To save time and resources, we used a convenience sampling method to collect the questionnaires. Two data collectors with experience in education and research administered the survey and provided explanations to participants when they had any inquiries. The questionnaire was translated into Vietnamese and reviewed by an expert fluent in both Vietnamese and English. The investigation took place from December 28, 2025, to January 10, 2026. After completing the official survey, 20 invalid responses were removed, resulting in 370 valid responses.

4. Results

4.1. Sample demographic characteristics

Among the 370 respondents, freshmen accounted for nearly half of the sample (48.6%), followed by juniors (18.4%) and seniors (33.0%). Males comprised 69.7% of the participants, and most students came from the Central region (90.8%). Among various types of AI educational platforms, ChatGPT was the most popular (74.3%), followed by Gemini (22.4%) (see Table 1).

Table 1. Respondent Characteristics (N=370)

Student year	Frequency	%	Region	Frequency	%
Freshman	180	48.6	Northern	9	2.4
Sophomore	58	15.7	Central	336	90.8
Junior	68	18.4	Southern	4	1.1
Senior	64	17.3	Other	21	5.7
Gender	**Frequency**	**%**	**AI-education platform**	**Frequency**	**%**
Male	258	69.7	ChatGPT	275	74.3
Female	110	29.7	DeepSeek	9	2.4
Other	2	0.5	Gemini	83	22.4
			Other	3	0.8

4.2. Examination of the construct validity

According to Harman's single-factor test, a single-factor model was estimated by loading all scale items into a single construct, and an unrotated factor analysis was then conducted using SPSS. The finding indicated that eight factors were extracted from 25 observed items, with the variance explained by the first factor being 46.25% (< 50%) [44]. Accordingly, no evidence of common method bias was detected in the sample.

Table 2 exhibits satisfactory composite reliability (CR) values that range from 0.888 to 0.911 (> 0.70). It indicates satisfactory internal consistency. All outer loadings range from 0.734 to 0.870 (> 0.70). The average variance extracted (AVE) values range from 0.621 to 0.720, providing the established benchmark of 0.50, thus meeting the benchmarks used to assess convergent validity [25]

[26]. The Fornell–Larcker criterion was applied to assess discriminant validity, which shows that the square root of the AVE for each construct exceeds its correlations with all other constructs. Similarly, all HTMT values are below 0.90, further supporting the discriminant validity [19] (see Table 3).

Table 2. Outer loading, CR, and AVE

Factors	Outer loading	Cronbach's Alpha	CR	AVE
Social norms		0.846	0.891	0.621
SI1	0.758			
SI2	0.774			
SI3	0.836			
SI4	0.833			
SI5	0.734			
Anthropomorphism		0.848	0.898	0.688
ANTH1	0.814			
ANTH2	0.854			
ANTH3	0.865			
ANTH4	0.781			
Perceived ease of use		0.831	0.888	0.664
EE1	0.757			
EE2	0.851			
EE3	0.841			
EE4	0.807			
Perceived usefulness		0.845	0.896	0.682
PE1	0.815			
PE2	0.847			
PE3	0.848			
PE4	0.793			
Trust in AI		0.859	0.904	0.703
TRUST1	0.836			
TRUST2	0.859			
TRUST3	0.858			
TRUST4	0.799			
Intention to use generative AI		0.87	0.911	0.72
INT1	0.846			
INT2	0.87			
INT3	0.861			
INT4	0.818			

Table 3. Discriminant Validity Analysis

Fornell-Larcker criterion						
	ANTH	EE	INT	PE	SI	TRUST
ANTH	0.829					
EE	0.437	0.815				
INT	0.592	0.552	0.849			
PE	0.676	0.519	0.587	0.826		
SI	0.684	0.555	0.711	0.738	0.788	
TRUST	0.722	0.522	0.679	0.731	0.76	0.838
HTMT						
	ANTH	EE	INT	PE	SI	TRUST
ANTH						
EE	0.517					
INT	0.69	0.644				
PE	0.797	0.615	0.682			
SI	0.806	0.657	0.827	0.873		
TRUST	0.846	0.612	0.782	0.858	0.89	

Note: ANTH (anthropomorphism); EE (perceived ease of use); INT (Intention to use generative AI); PE (perceived usefulness); SI (Social norms); TRUST (Trust in AI)

Furthermore, the study elucidated the variance inflation factor (VIF) to detect potential collinearity issues [4] and [29] suggested that the values of VIF must be < 10, and VIF values fell within acceptable limits, validating the absence of multicollinearity (Table 4).

Table 4: The variance inflation factor

Hypotheses	**VIF**
Anthropomorphism → Perceived ease of use	1.879
Anthropomorphism → Perceived usefulness	1.879
Anthropomorphism → Trust in AI	1.879
Social norms → Perceived ease of use	1.879
Social norms → Perceived usefulness	1.879
Social norms → Trust in AI	1.879
Perceived ease of use → Intention to use generative AI	1.456
Perceived usefulness → Intention to use generative AI	2.271
Trust in AI -> Intention to use generative AI	2.282

4.3. Structural model

Perceived usefulness, trust in AI, and intention to use generative AI achieve acceptable explanatory power (R^2) of 60%, 65.4%, and 52.1% (> 33%) [12]. However, the R^2 value for perceived ease of use is relatively modest at 31.4%. According to [49], the explanatory power of endogenous variables (R^2) can be interpreted as substantial (0.26), moderate (0.13), and weak (0.02). Therefore, the R^2

value for perceived ease of use in this study can be considered acceptable. Seven hypotheses were supported at the 0.05 and 0.01 significance levels [26]. First, social norms serve as a significant predictor of perceived usefulness (H1: beta = 0.519, p < 0.01), perceived ease of use (H2: beta = 0.481, p < 0.01), and trust in AI (H3: beta = 0.501, p < 0.01). Furthermore, anthropomorphism emerges as a significant determinant of perceived usefulness (H4: beta = 0.321, p < 0.01) and trust in AI (H6: beta = 0.379, p < 0.01) but does not emerge as a determinant of perceived ease of use (H5: beta = 0.108, p = 0.097). Finally, perceived usefulness does not significantly affect intention to use generative AI (H7: beta = 0.121, p = 0.069). In contrast, perceived ease of use (H8: beta = 0.248, p < 0.01) and trust in AI (H9: beta = 0.461, p < 0.01) are identified as positive drivers of intention to use generative AI (See Table 5 and Figure 2).

Table 5. Hypothesis results

No	Hypotheses	Beta	p
H1	Social norms → perceived usefulness	0.519	< 0.01
H2	Social norms → perceived ease of use	0.481	< 0.01
H3	Social norms → trust in AI	0.501	< 0.01
H4	Anthropomorphism → perceived usefulness	0.321	< 0.01
H5	Anthropomorphism → perceived ease of use	0.108^{ns}	0.097
H6	Anthropomorphism → trust in AI	0.379	< 0.01
H7	Perceived usefulness → Intention to use generative AI	0.121^{ns}	0.069
H8	Perceived ease of use → Intention to use generative AI	0.248	< 0.01
H9	Trust in AI → Intention to use generative AI	0.461	< 0.01

Note: ns: non-significant

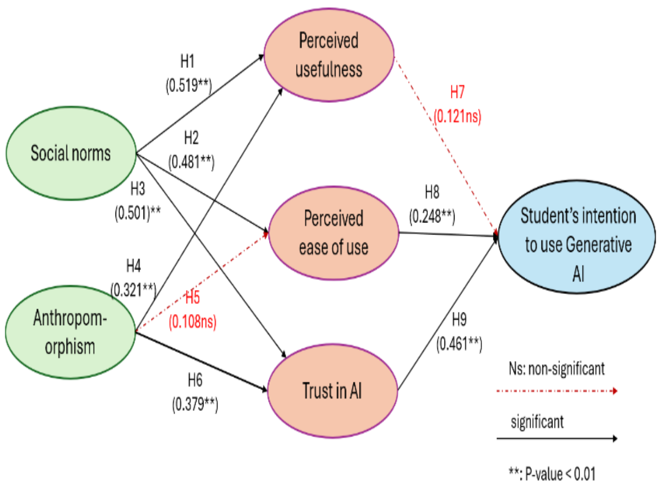

Figure 2. The result of research model

5. Conclusion

5.1. Discussion

The results indicate a complex process underlying students' intention to use advanced AI-driven learning tools. Compared with anthropomorphism, social norms exert a stronger impact on perceived usefulness, perceived ease of use, trust in AI. This implies that students rely more on people around them and the broader social environment when evaluating AI, rather than on how human-like AI appears. The effects of social referents on utility, usability, and confidence in AI systems are comparable in magnitude. Prior studies have documented comparable results [8] [46]. They suggest that individuals in students' social circles (e.g., friends, family members, and lecturers) play a crucial role in helping students recognize that generative AI can enhance learning performance and can be used with relatively little effort, thereby strengthening trust in AI. This pattern may be explained by the characteristics of the sample, as most participants are first-year students who may have limited understanding and practical engagement with AI systems. Consequently, their perceptions and trust are more strongly shaped by the opinions and experiences of people around them than by a direct understanding of AI features.

Interestingly, personification did not significantly affect the perceived ease of use of AI. This result may be due to the study participants being digitally savvy students born into a technologically advanced age. For these learners, human-like traits do not necessarily simplify the interface; instead, such personification primarily indicates that the technology is effective for their learning and reinforces their belief in the system. Having long-term interactions with technology, these students possess a high level of digital literacy, making the perceived ease of use a negligible concern in their systematic adoption of AI.

Observed outcomes of anthropomorphic attributes on evaluations of perceived usefulness and trust in AI have been reported in earlier research [54]. These results suggest that human-like characteristics of AI enhance evaluations of functional value rather than simplicity of use, as users tend to focus more on outcomes and task performance than on the underlying operational processes. When AI systems exhibit human-like appearance, speech, or responses, users feel more familiar with the system, perceive it as easier to understand and more approachable, and consequently develop higher levels of trustworthiness in AI.

The effects of trust in AI and perceived ease of use on intention to use generative AI are supported by prior studies [50] [53]. Trust exerts the paramount driver on intention to use AI, exceeding the effect of effort expectancy. Trust functions as a psychological safeguard, enabling users to accept the risks and uncertainties associated with AI. When students have a high level of confidence, they are more inclined to intend to use AI regardless of its perceived functional value. Ease-of-use beliefs further shape intention to use generative AI, as systems that are easy to use require less learning effort and generate lower levels of stress. This ease of interaction encourages users to experiment with AI, thereby supporting adoption.

Although perceived usefulness does not significantly impact students' intentions to use generative AI, unlike findings in prior research on other technologies, this result is consistent with some studies in the AI context. For example, perceived usefulness was found to have no significant impact on students' behavioral intention to use ChatGPT [5]. Similarly, no significant effect was observed on individuals' intention to use AI virtual assistants [20]. This finding reveals that AI is increasingly becoming a standard utility in daily life. When a technology becomes normalized, its usefulness may function as a hygiene factor rather than a primary driver of behavioral intention.

5.2. Theoretical implications

By adopting the S-O-R framework, this study makes several theoretical contributions to AI literature, particularly in the educational context. First, this study addresses an important gap by examining students' intention to use AI to support their learning activities. Most existing research has focused on the AI usage behavior of commercial customers or employees, whereas the impact of AI is expanding across sectors. Particularly, AI has been confirmed to play a crucial role in education [67]. This study examines the process through which students form their intention to use AI. This is a complex process that involves the influence of external environments, system attributes, and cognitive factors.

Second, this study reveals that external environments serve as the foundational mechanism shaping students' behavioral intention to use AI. Specifically, for students, especially first-year students who have limited experience or knowledge of AI, social influence from friends, family members, and significant others plays a critical role in shaping their perceptions of AI's functionality and trustworthiness. Additionally, as AI represents a form of human-like intelligence, this study also examines anthropomorphism as a key system attribute. Anthropomorphic features enable students to perceive AI as interacting in a manner like a human assistant, providing personalized information. Consequently, these human-like characteristics enhance students' perceptions of AI usefulness and strengthen their trust in technology. By demonstrating that anthropomorphism significantly enhances trustworthiness but does not directly influence the intention to use generative AI, these findings clarify the distinct psychological mechanisms through which human-like cues operate. Furthermore, this result suggests that generative AI in education should be conceptualized not merely as a productive tool but also as an educational partner that shapes users' psychological processes, thereby enriching emerging theoretical perspectives on human–AI interaction in pedagogical settings.

Like conventional technologies, the perceived usefulness and ease of use of AI significantly shape students' intention to use generative AI. Importantly, this study reveals that trust exerts the strongest influence on students' responses to generative AI. While many prior studies treat trust as either an independent variable or an outcome, few conceptualize trust as a psychological mediator that explains how design-related and social stimuli translate into behavioral intentions. In this study, students' trust, formed through social norms and anthropomorphic features, significantly enhances their intention to use generative AI.

5.3. Practical implications

Based on the results, this study proposes several practical implications. First, because social norms exert the strongest effect on students' perceptions of AI's functional aspects as well as their trust, policymakers and educational administrators should leverage peer influence. Universities should encourage students who have positive experiences with AI, particularly those who effectively apply generative AI in their studies, to share how they use this technology for academic tasks and assignments. In addition, institutions can utilize student ambassadors to promote AI-based learning platforms. Furthermore, universities should use social media as a communication channel to share tips, best practices, and reliable information related to AI, thereby enhancing students' trust in this technology.

The more generative AI can provide personalized services or information, the more likely students are to prefer using it and develop greater trust in AI. Therefore, policymakers and system designers should enhance the human-like traits of AI. First, AI student communication can be anthropomorphized by using natural and friendly language. Furthermore, AI should be capable of posing open-ended questions, avoiding rigid interactions, and engaging in dialogue that resembles human-to-human communication. It is also important to use forms of address that are appropriate to students' cultural contexts. Importantly, personalization should be further strengthened. AI systems can be designed to remember users' learning goals, proficiency levels, and learning styles, and to provide examples that are relevant to specific subjects or personal interests.

Since trust has the paramount direct effect on students' responses to generative AI, it is essential to implement multiple strategies to enhance trust, thereby strengthening students' intention to use generative AI. First, transparency and explainability should be emphasized by briefly explaining why the AI provides a particular suggestion or conclusion, and by indicating the level of certainty and the limitations of the response. When students gain a clearer understanding of how AI operates and make decisions, their trust in technology is significantly enhanced. Additionally, responsible anthropomorphism should be prioritized. The AI interface should incorporate an appropriate level of social cues to appear approachable without being misleading or deceptive. Furthermore, AI systems should be designed to be easy to use, as usability encourages continued use and reinforces students' trust in the technology.

Universities can collaborate with tourism and hospitality businesses to implement generative AI in practical student training by integrating it into simulated learning experiences. Educators and policymakers can design learning projects that facilitate student engagement with generative AI applications in customer service contexts. Through these projects, students can practice assisting customers and engaging with diverse cultural scenarios. Such an approach may enhance students' trust in AI by fostering experiential learning and hands-on engagement. Importantly, universities should provide clear orientation to students that AI operates as a facilitative instrument rather than a replacement for critical thinking. Training programs should encourage the multicentred assessment of AI-generated content, raise awareness of potential biases, and address knowledge distortions produced by AI systems. In parallel, institutions should strengthen students' understanding of the responsible use of AI.

5.4. Limitations and recommendations for future research

Despite its contributions, the current work is subject to certain shortcomings. First, the external environment is limited to social influence and anthropomorphism. Future studies could incorporate additional environmental factors, such as university regulations, institutional support, or data security policies. Second, this research focuses only on students in tourism programs at Duy Tan University. Future research could extend the sample to students from other disciplines, such as technology, management, or engineering, as well as to other universities or educational contexts. Moreover, rather than focusing solely on intention to use AI, future studies could examine long-term engagement patterns, such as user satisfaction or continued usage intention. Finally, this research has not yet included factors that specifically explain the educational context, particularly in tourism pedagogy. As a result, it is limited in translating AI use in academic settings into tourism-related digital literacy. Therefore, this represents an important research gap for future studies.

References

[1] Ackermann H, Henke A, Chevalère J, Yun HS, Hafner VV, Pinkwart N, Lazarides R. Physical embodiment and anthropomorphism of AI tutors and their role in student enjoyment and performance. *NPJ Sci Learn*. 2025;10(1):1.

[2] Afroogh S, Akbari A, Malone E, Kargar M, Alambeigi H. Trust in AI: progress, challenges, and future directions. *Humanit Soc Sci Commun*. 2024; 11(1):1–30.

[3] Ajenaghughrure IB, Sousa SC, Kosunen IJ, Lamas D. Predictive model to assess user trust: a psycho-physiological approach. In: *Proceedings of the 10th Indian Conference on Human-Computer Interaction*; November 2019; Goa, India. New York (NY): ACM; 2019. p. 1–10.

[4] Aiken LS, West SG, Reno RR. *Multiple regression: Testing and interpreting interactions*. Thousand Oaks (CA): Sage Publications; 1991.

[5] Alshammari SH, Krishna S, Alghamdi BA. The mediating role of engagement in the relationship between performance expectancy, effort expectancy, and students' behavioral intention to use ChatGPT. *Acta Psychol*. 2026;263:106270.

[6] Amoozadeh M, Daniels D, Nam D, Kumar A, Chen S, Hilton M, Alipour MA. Trust in generative AI among students: an exploratory study. In: *Proceedings of the 55th ACM Technical Symposium on Computer Science Education (SIGCSE)*; March 2024; Portland, OR, USA. New York (NY):

[7] Alsaad A. The dual effect of anthropomorphism on customers' decisions to use artificial intelligence devices in hotel services. *J Hosp Mark Manag*. 2023; 32(8):1048–1076.

[8] Baabdullah AM. Consumer adoption of mobile social network games (M-SNGs) in Saudi Arabia: the role of social influence, hedonic motivation and trust. *Technol Soc*. 2018; 53:91–102.

[9] Blut M, Wang C, Wünderlich NV, Brock C. Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. *J Acad Mark Sci*. 2021; 49(4):632–658.

[10] Chai CS, Lin PY, Jong MSY, Dai Y, Chiu TK, Huang B. Factors influencing students' behavioral intention to continue artificial intelligence learning. In: *Proceedings of the International Symposium on Educational Technology (ISET)*; August 2020; Bangkok, Thailand. Piscataway (NJ): IEEE; 2020. p. 147–150.

[11] Chen QQ, Park HJ. How anthropomorphism affects trust in intelligent personal assistants. *Ind Manag Data Syst*. 2021; 121(12):2722–2737.

[12] Chin WW. The partial least squares approach to structural equation modeling. *Mod Methods Bus Res*. 1998; 295(2):295–336.

[13] Choung, H., David, P., & Ross, A. (2023). Trust and ethics in AI. *Ai & Society*, *38*(2), 733-745. https://doi.org/10.1007/s00146-022-01473-4

[14] Chudhery MAZ, Safdar S, Huo J, Rehman HU, Rafique R. Proposing and empirically investigating a mobile-based outpatient healthcare service delivery framework using stimulus–organism–response theory. *IEEE Trans Eng Manag*. 2021; 70(8):2668–2681.

[15] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q*. 1989; 13(3):319–340.

[16] Della Corte V, Sepe F, Gursoy D, Prisco A. Role of trust in customer attitude and behaviour formation towards social service robots. *Int J Hosp Manag*. 2023; 114:103587.

[17] Donovan RJ, Rossiter JR. *Retailing: Critical Concepts*. Vol. 3. London: Routledge; 2002. Chapter 2, Store atmosphere: an environmental psychology; p. 77–89.

[18] Dowling M, Lucey B. ChatGPT for (finance) research: The Bananarama conjecture. *Finance Res Lett*. 2023;53:103662.

[19] Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. *J Mark Res*. 1981; 18(1):39–50.

[20] García de Blanes Sebastián M, Sarmiento Guede JR, Antonovica A. Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Front Psychol*. 2022;13:993935.

[21] Government Digital Service. Generative AI: product safety standards. 2026. Available from: Government Digital Service. Accessed March 3, 2026. Available at: https://www.gov.uk/government/publications/generative-ai-product-safety-standards/generative-ai-product-safety-standards

[22] Goldman Sachs. Generative AI could raise global GDP by 7%. 2023. Available from: Goldman Sachs Insights. Accessed January 12, 2026. Available at: https://www.goldmansachs.com/insights/pages/generative-aicould-raise-global-gdp-by-7-percent.html

[23] Guilherme A. AI and education: the importance of teacher and student relations. *AI Soc*. 2019; 34(1):47–54.

[24] Gursoy D, Chi OH, Lu L, Nunkoo R. Consumers acceptance of artificially intelligent (AI) device use in service delivery. *Int J Inf Manage*. 2019;49:157–169.

[25] Hair JF Jr, Matthews LM, Matthews RL, Sarstedt M. PLS-SEM or CB-SEM: updated guidelines on which method to use. *Int J Multivar Data Anal*. 2017; 1(2):107–123.

[26] Henseler J, Ringle CM, Sinkovics RR. *Advances in International Marketing*. Vol. 20. Bingley: Emerald Group Publishing; 2009. Chapter 13, The use of partial least squares path modeling in international marketing; p. 277–319.

[27] Heung YME, Chiu TK. How ChatGPT impacts student engagement: a systematic review and meta-analysis study. *Comput Educ Artif Intell*. 2025; 8:100361.

[28] Islam JU, Rahman Z. The impact of online brand community characteristics on customer engagement: an application of the stimulus–organism–response paradigm. *Telemat Inform*. 2017; 34(4):96–109.

[29] Iqbal S, Moleiro Martins J, Nuno Mata M, Naz S, Akhtar S, Abreu A. Linking entrepreneurial orientation with innovation performance in SMEs: the role of organizational commitment and transformational leadership using smart PLS-SEM. *Sustainability*. 2021;13(8):4361.

[30] Koo B, Curtis C, Ryan B. Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *Int J Hosp Manage*. 2021;95:102763

[31] Krieger JB, Bouder F, Wibral M, Almeida RJ. A systematic literature review on risk perception of Artificial Narrow Intelligence. J Risk Res. 2024;1–19

[32] Lee S, Ha S, Widdows R. Consumer responses to high-technology products: product attributes, cognition, and emotions. *J Bus Res*. 2011; 64(11):1195–1200.

[33] Lei SI, Shen H, Ye S. A comparison between chatbot and human service: customer perception and reuse intention. *Int J Contemp Hosp Manag*. 2021; 33(11):3977–3995.

[34] Letheren K, Martin BA, Jin HS. Effects of personification and anthropomorphic tendency on destination attitude and travel intentions. *Tour Manage*. 2017;62:65–75.

[35] Li M, Suh A. Anthropomorphism in AI-enabled technology: a literature review. *Electron Mark*. 2022; 32(4):2245–2275.

[36] Lim WM, Gunasekara A, Pallant JL, Pallant JI, Pechenkina E. Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *Int J Manage Educ*. 2023;21(2):100790.

[37] Malfatti FI. ChatGPT, education, and understanding. *Soc Epistemol*. 2025:1–15.

[38] Masaracchia A, Bui TT. The role of metaverse in training and educational context: potentialities, use-cases, and research directions. *EAI Endorsed Trans Tour Technol Intell*. 2025;2(1).

[39] Marrone R, Taddeo V, Hill G. Creativity and artificial intelligence—a student perspective. *J Intell*. 2022; 10(3):65.

[40] Mehrabian A, Russell JA. *An approach to environmental psychology*. Cambridge (MA): MIT Press; 1974.

[41] Michel-Villarreal R, Vilalta-Perdomo E, Salinas-Navarro DE, Thierry-Aguilera R, Gerardou FS. Challenges and opportunities of generative AI for higher education as explained by ChatGPT. *Educ Sci*. 2023;13(9):856.

[42] Mittal U, Sai S, Chamola V, Sangwan D. A comprehensive review on generative AI for education. *IEEE Access*. 2024; 12:142733–142759.

[43] Naudé W, Dimitri N. The race for an artificial general intelligence: implications for public policy. *AI Soc*. 2020;35(2):367–379.

[44] Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: A critical review of the literature and recommended remedies. J Appl Psychol. 2003;88(5):879–903.

[45] Pallathadka H, Sonia B, Sanchez DT, De Vera JV, Godinez JAT, Pepito MT. Investigating the impact of artificial intelligence in education sector by predicting student performance. *Mater Today Proc*. 2022; 51:2264–2267.

[46] Pan W, Altshuler Y, Pentland A. Decoding social influence and the wisdom of the crowd in financial trading network. In: *Proceedings of the International Conference on Privacy, Security, Risk and Trust and the International Conference on Social Computing*; September 2012; Amsterdam, The Netherlands. Piscataway (NJ): IEEE; 2012. p. 203–209.

[47] Pandita S, Mishra HG, Chib S. Psychological impact of COVID-19 crises on students through the lens of the stimulus–organism–response (SOR) model. *Child Youth Serv Rev*. 2021; 120:105783.

[48] Polyportis A, Pahos N. Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy. *Behav Inf Technol*. 2025;44(2):315–336.

[49] Rahman IA, Memon AH, Abd Karim AT. Examining factors affecting budget overrun of construction projects undertaken through management procurement method using PLS-SEM approach. *Procedia Soc Behav Sci*. 2013;107:120–128.

[50] Rahi S, Othman Mansour MM, Alghizzawi M, Alnaser FM. Integration of UTAUT model in internet banking adoption context: the mediating role of performance expectancy and effort expectancy. *J Res Interact Mark*. 2019; 13(3):411–435.

[51] Reinecke MG, Ting F, Savulescu J, Singh I. The double-edged sword of anthropomorphism in LLMs. In: *Proceedings*. Proceedings of the Conference; February 2025; Basel, Switzerland. Basel: MDPI; 2025. p. 4.

[52] Teo TSH, Lim VKG, Lai RYC. Intrinsic and extrinsic motivation in internet usage. *Omega*. 1999; 27(1):25–37.

[53] Tran AQ, Nguyen LH, Nguyen HSA, Nguyen CT, Vu LG, Zhang M, Ho CS. Determinants of intention to use artificial intelligence-based diagnosis support system among prospective physicians. *Front Public Health*. 2021; 9:755644.

[54] Troshani I, Rao Hill S, Sherman C, Arthur D. Do we trust in AI? Role of anthropomorphism and intelligence. *J Comput Inf Syst*. 2021; 61(5):481–491.

[55] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. *MIS Q*. 2003; 27(3):425–478.

[56] Silvi M, Padilla E. Pro-environmental behavior: social norms, intrinsic motivation and external conditions. *Environ Policy Gov*. 2021; 31(6):619–632.

[57] Shamim S, Yang Y, Zia NU, Khan Z, Shariq SM. Mechanisms of cognitive trust development in artificial

intelligence among front line employees: An empirical examination from a developing economy. *J Bus Res*. 2023;167:114168
[58] Sharma S, Islam N, Singh G, Dhir A. Why do retail customers adopt artificial intelligence (AI)-based autonomous decision-making systems? *IEEE Trans Eng Manag*. 2022; 71:1846–1861.
[59] Skinner BF. The generic nature of the concepts of stimulus and response. *J Gen Psychol*. 1935; 12(1):40–65.
[60] Spatola N, Wudarczyk OA. Implicit attitudes towards robots predict explicit attitudes, semantic distance between robots and humans, anthropomorphism, and prosocial behavior: from attitudes to human–robot interaction. *Int J Soc Robot*. 2021; 13(5):1149–1159.
[61] Wang Y. Emotional dependence path of artificial intelligence chatbot based on structural equation modeling. *Procedia Comput Sci*. 2024;247:1089–1094.
[62] Wang YM, Wei CL, Lin HH, Wang SC, Wang YS. What drives students' AI learning behavior: a perspective of AI anxiety. *Interact Learn Environ*. 2024; 32(6):2584–2600.
[63] Wong CUI, Ren L, Chen PJ, Chen X, Zhang H. Assessing tourism and hospitality students' intention to use ChatGPT. *J Hosp Tour Educ*. 2025:1–14.
[64] Wu R, Yu Z. Do AI chatbots improve students' learning outcomes? Evidence from a meta-analysis. *Br J Educ Technol*. 2024; 55(1):10–33.
[65] Younas M, El-Dakhs DAS, Noor U. The impact of artificial intelligence-based learning tools in academic innovation: a review of DeepSeek, GPT, and Gemini (2020–2025). *Front Educ*. 2025; 10:1689205.
[66] Yu L, Li Y. Artificial intelligence decision-making transparency and employees' trust: the parallel multiple mediating effect of effectiveness and discomfort. *Behav Sci*. 2022; 12(5):127.
[67] Zhai X, Chu X, Chai CS, Jong MSY, Istenic A, Spector M, et al. A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*. 2021; 2021(1):8812542.
[68] Zhu Z, Hall CM, Koupaei SN, Lin F, Wang Z. Influence of AI on usage intention in tourism and hospitality education: the mediating role of perceived trust. *Curr Issues Tour*. 2026;1–14.
[69] Zhu CZG, Hall CM, Fong LHN, Lin F, Naderi Koupaei S. Examining the effects of ChatGPT on tourism and hospitality student responses through integrating technology acceptance model. *Int J Tour Res*. 2024;26(4):e2727.