Modeling the determinants of HEI students' continuance intention to use ChatGPT for learning: a stimulus–organism–response approach

Cong Doanh Duong
National Economics University, Hanoi, Vietnam

Journal of Research in Innovative Teaching & Learning

Received 11 January 2024
Revised 15 February 2024
Accepted 3 April 2024

Abstract

Purpose – Although previous research has acknowledged the significance of comprehending the initial acceptance and adoption of ChatGPT in educational contexts, there has been relatively little focus on the user's intention to continue using ChatGPT or its continued usage. Therefore, the current study aims to investigate the students' continuance intentions to use ChatGPT for learning by adopting the stimulus–organism–response (SOR) model.

Design/methodology/approach – This study has employed the SOR model to investigate how UTAUT factors (such as performance expectancy, facilitating conditions, effort expectancy and social influence) influence the cognitive responses of students (e.g. trust in ChatGPT and attitude towards ChatGPT), subsequently shaping their behavioral outcomes (e.g. the intention to continue using ChatGPT for study). A sample of 392 higher students in Vietnam and the PLS-SEM method was employed to investigate students' continuance intention to use ChatGPT for learning.

Findings – This study reveals that students' continuance intention to use ChatGPT for learning was directly affected by their attitude toward ChatGPT and trust in ChatGPT. Meanwhile, their attitude toward ChatGPT was built on effort expectancy, social influence, and facilitating conditions and trust in ChatGPT was developed from effort expectancy and social influence.

Originality/value – By extending the analysis beyond initial acceptance, this research provides valuable insights into the factors that influence the sustained utilization of ChatGPT in an educational environment.

Keywords ChatGPT, Stimulus–organism–response model, UTAUT model, Continuation intention, Trust in ChatGPT

Paper type Research paper

1. Introduction

The ongoing progress in natural language processing (NLP) technologies has led to the emergence of highly advanced language models, with the GPT-3.5-based chatbot, known as ChatGPT, standing out as a prominent example (Menon and Shilpa, 2023; Wong *et al.*, 2023). These models demonstrate their capability to comprehend and produce text that closely resembles human language, effectively handling a wide range of tasks including automatic summarization, machine translation, question answering, and more (Bin-Nashwan *et al.*, 2023). The arrival of ChatGPT can be likened to the onset of the "strong AI era," signifying a remarkable stride forward in the field of artificial intelligence (AI). This groundbreaking

This research is funded by National Economics University, Hanoi, Vietnam.

Journal of Research in Innovative Teaching & Learning
Emerald Publishing Limited
2397-7604
DOI 10.1108/JRIT-01-2024-0006

development carries the potential to effectively tackle a multitude of constraints commonly associated with traditional AI systems (Duong *et al.*, 2023a). ChatGPT stands out due to its exceptional general AI capabilities and expertise in NLP, making it adaptable and beneficial across a broad spectrum of domains. These domains include but are not confined to fields like healthcare, education, academic research, and many more (Dwivedi *et al.*, 2023). One such domain that has witnessed the transformative potential of ChatGPT is students' learning (Anders, 2023).

In contemporary times, students are frequently labeled as "millennials" or "digital natives" because of their inclination to seamlessly incorporate new technologies into various facets of their daily lives, including the realm of education (Anega and Alemu, 2023). Language models like ChatGPT have seen a growing utilization across different educational levels, spanning from primary and secondary schools to tertiary and higher education environments (Tiwari *et al.*, 2023). The core objective behind the incorporation of these language models is to enhance the efficiency of students' learning experiences and elevate the quality of their outcomes. For instance, these models have the capacity to offer suggestions for syntactic and grammatical improvements (Lim *et al.*, 2023). Additionally, these models are capable of generating summaries and text outlines, which can be particularly helpful for higher education students in swiftly grasping the central concepts within a text and organizing their ideas for the purpose of writing (Qi *et al.*, 2023). Regrettably, there remains a scarcity of comprehensive studies that delve into how students are embracing ChatGPT as a learning tool (Duong *et al.*, 2023a; Kasneci *et al.*, 2023; Tiwari *et al.*, 2023). In addition, although previous research has acknowledged the significance of comprehending the initial acceptance and adoption of ChatGPT in educational contexts (Bin-Nashwan *et al.*, 2023; Lai *et al.*, 2023), there has been relatively little focus on the user's intention to continue using ChatGPT or its continued usage. This highlights the pressing necessity for additional research aimed at uncovering the factors that might influence students' intentions when it comes to the adoption and utilization of this state-of-the-art technology for their educational pursuits (Duong *et al.*, 2023a).

It is remarkable that there is a dearth of research on the potential implications of Generative AI on the learning sector. To leverage the full potential of ChatGPT and other Generative AI tools in learning and education, it is crucial to comprehend not just the initial adoption and utilization of these tools by users but also their prolonged usage. Consequently, a comprehensive research agenda is imperative, taking into account the broader context of learning and the multitude of factors that impact students' decisions to persist with ChatGPT in this domain.

To fill this gap, the current study aims to investigate the students' continuance intentions to use ChatGPT for learning by adopting the stimulus–organism–response (SOR) model. The SOR model sets itself apart from other theories related to the diffusion of innovation by providing a thorough and holistic framework for examining the elements that shape the uptake of cutting-edge technology (Upadhyay and Kamble, 2023). The built-in cause-and-effect structure of the SOR model renders it a preferred choice among scholars who aim to investigate the adoption of technology (Chakraborty *et al.*, 2023). Therefore, it can be an effective model to explain students' continuance intentions to use ChatGPT for their learning. To be specific, within our model, we employ the SOR framework in the following manner: stimulus (S) encompasses the unified theory of acceptance and use of technology (UTAUT) factors, encompassing performance expectancy, effort expectancy, social influence, and facilitating conditions. The organism (O) encompasses an individual's attitude toward ChatGPT and their trust in ChatGPT. Lastly, the response (R) encompasses the behavioral intentions, specifically focusing on the continuance usage intentions of ChatGPT for educational purposes.

2. Literature review and hypotheses

2.1 Continuance usage intentions of ChatGPT for study

Continuance intention is a term that describes the likelihood of users intending to use specific information technology systems in the future (Bhattacherjee, 2001). The behavior of users to continue using a service is an essential aspect that has been extensively studied in the field of information systems (Dağhan and Akkoyunlu, 2016). As a result, a significant amount of research has been conducted to examine the various factors that influence the intention of users to continue using different online technologies, such as mobile apps (Foroughi *et al.*, 2023), online services (Dağhan and Akkoyunlu, 2016), and chatbots (Ashfaq *et al.*, 2020).

This study specifically defines continuance intention for using ChatGPT for study as students' intention to persist in using and benefiting from ChatGPT for academic purposes. Despite scholars emphasizing the importance of comprehending the impact of Generative AI on educational decision-making, there is a scarcity of empirical studies in this field (Duong *et al.*, 2023a). While previous research has acknowledged the significance of understanding the initial adoption and acceptance of educational technologies, the continuity of usage, or the users' intention to continue employing ChatGPT in the educational context, remains a relatively unexplored area.

2.2 Research framework: stimulus–organism–response theory

The SOR model originated from the stimulus–response theory and was initially devised by Mehrabian and Russell (1974) within the field of environmental psychology. This framework posits that environmental stimuli influence individuals' cognition, emotions, and behaviors (Zhu *et al.*, 2019). The fundamental mechanism of the relationship within the SOR framework revolves around how stimuli impact an individual's emotions and cognitive processes, subsequently shaping their responses (Xie *et al.*, 2023). Specifically, stimuli (S) encompass the broader concept of an individual's surroundings, serving as the driving force behind their internal emotional states; organisms (O) pertain to an individual's inner perception after encountering stimuli in a given context, just before they make actual responses; and responses (R) denote an individual's natural reactions following the perception of these stimuli (Duong, 2022).

The SOR model has been applied in various scenarios, including the field of human–computer interaction. Previous researchers have extensively investigated the interaction between humans and computers based on this model (Xie *et al.*, 2023). For example, Cheng *et al.* (2022) employed the SOR model to gain essential insights into how consumers perceive and respond to text-based chatbots. In a similar vein, Sung *et al.* (2021) examined the influence of interactive AI on consumers' intentions to share experiences and make purchases with social groups, using the SOR model as the basis for their study. Liu and Huang (2023) also applied the SOR model to illustrate how virtual reality videos, specifically virtual tour simulations, influence users' varying levels of satisfaction. In summary, the SOR model has gained significant traction in the domain of human–computer interaction (Xie *et al.*, 2023; Xu *et al.*, 2020). Therefore, this study leverages the SOR model to explain the continuance usage intentions of ChatGPT for the study of students. In particular, utilizing the SOR framework within our model (depicted in Figure 1), the stimulus (S) represents the UTAUT factors, including performance expectancy, effort expectancy, social influence, and facilitating conditions. The organism (O) encompasses attitude toward ChatGPT and trust in ChatGPT. The response (R) encompasses the behavioral intentions, specifically continuance usage intentions of ChatGPT for study.

2.3 UTAUT factors as the stimulus

The UTAUT was introduced by Venkatesh *et al.* (2003), which is a theoretical framework developed to elucidate and predict the factors that influence users' acceptance and utilization

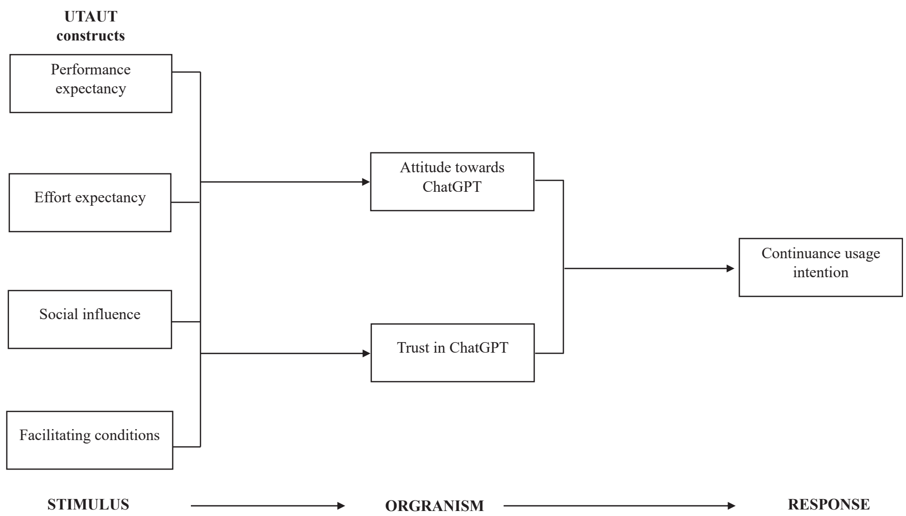


Figure 1.
The conceptual model

Source(s): Figure by authors'

of technology (Menon and Shilpa, 2023). UTAUT was developed based on various preexisting theories, including the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB). UTAUT integrates these theories and introduces four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh *et al.*, 2003). This model has found extensive application in both research and practical settings to steer the development and implementation of technology interventions. In the context of AI tools, UTAUT is also adaptable for assessing users' acceptance and utilization of AI tools (Venkatesh, 2021). The constructs within UTAUT can be modified to reflect the distinct features and capabilities of AI technology, thereby being employed to investigate emerging AI tools, such as chatbots (Balakrishnan *et al.*, 2022; Menon and Shilpa, 2023), mobile payment (m-payment) (Alkhowaiter, 2022; Leong *et al.*, 2021), and recommendation systems (Chen *et al.*, 2023).

In the UTAUT, Venkatesh *et al.* (2003) introduced the concept of performance expectancy as an individual's perception of how using a particular system will enhance their performance or bring about improvements. In essence, it addresses the degree to which users believe they will gain advantages and benefits from a specific technology (Hoi, 2020; Nikolopoulou *et al.*, 2021). In this study, performance expectancy pertains to higher education students and their perceptions of the advantages and benefits of integrating ChatGPT into their learning processes. This aspect delves into how students view ChatGPT as a tool that can enhance their academic performance, offering a range of advantages and benefits to their learning experiences.

Previous studies have demonstrated that performance expectancy is the most significant factor that leads individuals' attitudes toward technology. The ease of technology usage (i.e. its simplicity) and its potential utility (i.e. improved performance) can influence the attitudes of individuals (Dwivedi *et al.*, 2017). The more user-friendly and beneficial a technology is perceived to be, the more positive an attitude one will develop toward its usage (Park *et al.*, 2019). Therefore, a positive performance expectancy of ChatGPT will lead to a positive attitude toward using it. Furthermore, when individuals have high expectations regarding the performance of ChatGPT, believing that it can consistently provide accurate and valuable information, they are more likely to trust the system. Indeed, studies in the field of AI chatbots have revealed that a chatbot's capability to provide accurate responses to customer queries and offer valuable suggestions plays a pivotal role in cultivating trust in chatbots (Følstad *et al.*, 2018). In the ChatGPT context, students anticipate ChatGPT to effectively address their inquiries by furnishing valuable information in a top-notch interaction that is seamless, precise, and comprehensive (Duong *et al.*, 2023a). If ChatGPT consistently demonstrates its ability to meet or exceed these performance expectations, users are more likely to trust the system, relying on it for various tasks and information. Hence, we propose the following hypotheses:

H1. Performance expectancy positively affects (a) attitude toward ChatGPT and (b) trust in ChatGPT

Effort expectancy is another vital factor that influences one's behavioral intention towards technology. It refers to the level of ease associated with using the technology (Venkatesh *et al.*, 2003). In this study, effort expectancy reflects the user-friendliness associated with utilizing ChatGPT for educational purposes. Following previous research on AI adoption, effort expectancy emerges as a notably significant factor that impacts the choice to embrace AI technology (Alkhowaiter, 2022). Balakrishnan *et al.* (2022) reported that effort expectancy is positively related to attitude towards chatbot service interactions. Similarly, this study argues that effort expectancy plays a pivotal role in shaping an individual's attitude toward using ChatGPT. Indeed, when students find ChatGPT to be intuitive, user-friendly, and requiring minimal effort to interact with, their overall user experience becomes more efficient and convenient (Duong *et al.*, 2023b). Thus, their attitude toward using the system tends to be more positive. In contrast, if the technology is seen as cumbersome and demanding, users may develop a negative attitude, which can deter them from engaging with ChatGPT.

In addition, some previous research also suggested that effort expectation positively impacts user trust. In the mobile payment context, Yan and Yang (2015) argued that a mobile payment system that is user-friendly, featuring well-crafted interfaces and intuitive navigation, will showcase the competence and goodwill of service providers, consequently impacting user trust. Leong *et al.* (2021) also reported that effort expectancy has a significant impact on students' trust in m-payment. Therefore, this study expects the same principle to apply to ChatGPT, in which students' effort expectancy can have effects on their trust in ChatGPT. When students feel that the technology is straightforward and doesn't demand a significant amount of effort to achieve their learning goals, they are more likely to trust that it will reliably assist them in their academic pursuits. Hence, we propose the following hypotheses:

H2. Effort expectancy positively affects (a) attitude toward ChatGPT and (b) trust in ChatGPT.

Social influence is defined as the extent to which individuals place importance on the social aspects of adopting a specific technology (Verma and Sinha, 2018). While numerous studies have discovered that social influence can notably foster a positive behavioral intention toward a particular technology, there is a scarcity of research that has empirically investigated the contribution of social influence to the development of a positive attitude (Balakrishnan *et al.*, 2022). In the context of information technology adoption, Dwivedi *et al.* (2017) observed a significant connection between social influence and attitude toward technology. Also, Wood (2000) has proposed that persuasion and social influence carry a more substantial influence in shaping favorable or unfavorable attitudes and subsequent changes in attitude. Therefore, this study argues that social influence positively affects attitudes toward ChatGPT. When students perceive that their peers, colleagues, or social networks endorse and find value in ChatGPT, it can contribute to a more positive attitude toward the system.

Furthermore, this is also linked to a sense of trust and credibility in the technology and the belief that using ChatGPT aligns with social norms and expectations. Chaouali *et al.* (2016) stated that individuals who hold the belief that significant people in their lives, like family and friends, endorse their adoption of new products or services, are more likely to have trust in and a greater inclination to utilize these products and services. Additionally, in the field of sociology, the development of trust in a specific entity is shaped by cultural norms (Chen *et al.*, 2023). Put differently, individual trust is influenced by social influence. Therefore, this study argues that social influence positively affects trust in ChatGPT.

Based on the above arguments, we propose the following hypotheses:

H3. Social influence positively affects (a) attitude toward ChatGPT and (b) trust in ChatGPT

Facilitating conditions, as the fourth factor within the UTAUT model, encompass the requirements and assistance that a consumer perceives as available for carrying out an action (Venkatesh *et al.*, 2003). In this study, facilitating conditions assess students' perceptions about the requisite resources, knowledge, and support necessary for using ChatGPT in their academic pursuits. Balakrishnan *et al.* (2022) suggested that facilitating conditions can build a stronger attitude towards new technology. Indeed, when students perceive that they have access to the necessary resources, knowledge, and support to effectively utilize ChatGPT for their studies, their attitude toward using the technology becomes more positive, and they are more likely to engage in using technology (Menon and Shilpa, 2023; Cokins *et al.*, 2020). Additionally, the extent to which facilitating conditions are perceived by students also directly impacts their trust in ChatGPT. Individual trust is grounded in the belief that the presence of such facilitating conditions indicates a commitment to providing a secure, reliable, and supportive environment for users. In other words, when students are confident that the required infrastructure and assistance are in place, they are more inclined to trust that ChatGPT will consistently meet their needs and expectations (Cheng *et al.*, 2022).

Therefore, we propose the following hypotheses:

H4. Facilitating conditions positively affect (a) attitude toward ChatGPT and (b) trust in ChatGPT.

2.4 Organisms and behavioral responses

Attitude can be described as the degree of positive or negative emotions an individual links to their involvement in a particular action (Davis, 1989). Prior research has established a notable connection between attitude and continuance intention (Balakrishnan *et al.*, 2022; Manser Payne *et al.*, 2018). Wu and Chen (2017) also suggested that users often shape their ongoing behavior with a technology based on the sentiment they hold toward it. Thus, the present study, operating within the S–O–R paradigm, posits that in the context of using ChatGPT for learning purposes, fostering positive attitudes towards its utilization (organism) would lead to a heightened intention to continue using it (responses). Indeed, when students maintain a positive attitude, characterized by a favorable emotional disposition and a sense of satisfaction with their interactions with ChatGPT, they are more likely to express a strong intention to continue using the technology. Conversely, a negative attitude, marked by dissatisfaction or frustration, can deter students from pursuing further engagement with ChatGPT. Therefore, the attitude students hold towards ChatGPT significantly influences their commitment to persist in using the system as a valuable resource in their academic pursuits. Hence, we propose the following hypotheses:

H5. Attitude toward ChatGPT positively affects continuance usage intention.

Additionally, the exploration of trust in technology represents a significant research domain within the realm of human–computer interaction (Hyun Baek and Kim, 2023). Trust, positioned as the organism in the S–O–R paradigm, represents the perceived assurance of a technology's reliability and its capacity to fulfill promised services (Gao and Waechter, 2015). Existing research commonly supports the idea that the higher the level of trust in technologies, the more likely users are to continue using them (Cheng *et al.*, 2022). In the field of AI chatbots, previous research has suggested that having trust in AI can result in positive outcomes, including sustained usage (Gkinko and Elbanna, 2023). Therefore, this study posits that trust in ChatGPT acts as the organism, influencing students' responses in terms of continuance usage intention. When students perceive ChatGPT as a trustworthy and reliable tool for their academic needs, it instils a sense of confidence in the technology's ability to consistently deliver valuable assistance. This trust not only reduces doubts or concerns but also encourages students to maintain their engagement with ChatGPT over time. Therefore, we propose the following hypotheses:

H6. Trust in ChatGPT positively affects continuance usage intention.

3. Methods

3.1 Sampling and data collection

The current research employs a single cross-sectional approach, obtaining data through a survey method. The survey targeted students studying in the top three public universities in Hanoi according to their national university entrance scores. We randomly selected four classes from each university, considering the specific academic disciplines they represented. In addition, we requested valuable assistance from university lecturers and department chairs to streamline the survey questionnaire administration. Before answering the questionnaire, students were provided with a brief explanation of the research's purpose and the terms used in the questionnaires. All participants were informed that the survey was voluntary and for research purposes only.

The survey was carried out from April 10 to May 6, 2023. A total of 519 higher education students took part in the survey. Out of all the questionnaires distributed, 425 were successfully filled out by participants, constituting 81.89% of the total. However, 33 questionnaires were disqualified from further analysis due to incomplete responses, leaving us with a valid dataset of 392 responses (75.53%) with no missing data. The demographic characteristics of the survey participants are detailed in Table 1. More than half of the respondents self-identified as female, accounting for 50.8 and 49.2% as male. The predominant age group among the participants fell within the range of 21–23 years, and a significant proportion studied in the third year. Among the respondents, 55.8% are pursuing studies in economics and management, while the remaining 44.2% are enrolled in engineering and other fields.

3.2 Questionnaire design and measure

The questionnaire was structured into two distinct sections. The first is focused on collecting demographic information from the respondents, including age, gender, year of study, and field of study. The second part encompasses the constructs related to the perception of ChatGPT.

The scales employed in this survey were adapted and adopted from prior studies. Four stimuli, performance expectancy (4 items), effort expectancy (4 items), social influence (3 items), and facilitating conditions (4 items) were adapted from the research of Balakrishnan *et al.* (2022). Two organisms, trust in ChatGPT (4 items) and attitude toward ChatGPT

Variables	Category	Frequency	%
Gender	Male	193	49.2
	Female	199	50.8
Age	18–20	173	44.1
	21–23	191	48.7
	>23	28	7.1
Year of study	First-year	58	14.8
	Second year	139	35.5
	Third year	168	42.9
	Final year	27	6.9
Fields of study	Economics and management	200	51.0
	Engineering and others	192	49.0

Note(s): $N = 392$
Source(s): The author's elaborations based on the research data

Table 1.
The demographic characteristics of the survey participants

(3 items) were adapted from the research of Cheng *et al.* (2022) and Balakrishnan and Dwivedi (2021), respectively. And response, continuance intention (3 items), was adapted from the research of Ashfaq *et al.* (2020). All items were evaluated using a five-point Likert-type scale, ranging from "strongly disagree" to "strongly agree". This study was carried out in Vietnam. Therefore, the questionnaire was initially translated from English into Vietnamese and subsequently back-translated the Vietnamese version into English. The consistency between the two versions was meticulously verified.

3.3 Data analysis method
This research employed structural equation modeling (SEM) to explore the interconnected pathways within a multivariable model that incorporates latent constructs (Hair, 2020; Thi Tuyet Mai, 2019). Our empirical data, sourced from a questionnaire, provided the basis for this analysis. Due to the presence of formative constructs within the SEM, considerations regarding the nature of the collected data, the predictive focus of our research, and the complexity of our hypothesized model, we opted for partial least structural equation modeling (PLS-SEM) to test the proposed model (Hair, 2020). The data analysis was conducted using Smart PLS 4.0 software for implementation. In addition, the reliability, convergent validity, and discriminant validity of all constructs were examined before testing the research model. Cronbach's alpha and composite reliability (CR) values were employed to assess the internal consistency of the measures, while the average variance extracted (AVE) was used to test scale validity.

3.4 Common method bias
To mitigate potential issues with common method bias stemming from systematic biases, this study utilized Harman's single factor test and principal axis factoring analysis to assess the risk of CMB. This methodological approach is consistent with previous studies that have analyzed CMB. Following Harman's criterion, the presence of CMB is indicated if a single factor explains more than 50% of the variance (Harman, 1976). However, the findings revealed that a single factor accounted for only 44.6% of the variance, falling below the 50% threshold, which indicates the absence of common method bias in the dataset.

4. Results
4.1 Measurement model test
As presented in Table 2, Cronbach's alpha values for all constructs surpassed the commonly accepted threshold of 0.7 (Hair *et al.*, 2010). Additionally, all the CR scores were above 0.8, and

Constructs	Items	Codes	Mean	S.D.	λ	α	CR	AVE
Attitude towards ChatGPT	I like using ChatGPT to study	ATC1	3.444	0.7237	0.964	0.961	0.962	0.928
	I feel good about using ChatGPT to study	ATC2	3.436	0.6978	0.980			
	Overall, my attitude towards ChatGPT for study is favorable	ATC3	3.418	0.7105	0.945			
Continuance usage intention	I intend to continue using ChatGPT in the future	CI1	3.342	0.7367	0.850	0.891	0.901	0.822
	I will always try to use this ChatGPT to study in my daily life	CI2	3.327	0.7470	0.950			
	I will strongly recommend ChatGPT to other students	CI3	3.321	0.7695	0.917			
Facilitating conditions	ChatGPT provide have the resources necessary for study use	FC1	3.500	0.7603	0.952	0.968	0.968	0.912
	I have the knowledge necessary to use the ChatGPT for study use	FC2	3.495	0.7535	0.969			
	ChatGPT are more compatible for service use	FC3	3.467	0.7629	0.967			
	ChatGPT have service assistance in case of any system difficulties	FC4	3.480	0.7700	0.932			
Performance expectancy	I find ChatGPT useful in my daily study	PE1	2.885	1.0213	0.917	0.918	0.931	0.801
	Using ChatGPT helps me accomplish tasks more quickly	PE2	2.893	0.9955	0.923			
	Using ChatGPT increases my productivity in my study	PE3	3.031	0.9802	0.924			
	Using ChatGPT can save my time	PE4	3.270	0.8452	0.811			
Effort expectancy	Learning how to use ChatGPT would be easy for me	EE1	3.306	0.8174	0.951	0.966	0.966	0.907
	My interaction with ChatGPT during studying would be clear and understandable	EE 2	3.316	0.8040	0.957			
	I would find ChatGPT easy to use	EE3	3.311	0.7965	0.962			
	It would be easy for me to become skillful at using ChatGPT	EE4	3.304	0.8105	0.939			
Social influence	People who are important to me think that I should use ChatGPT to study	SI1	3.497	0.7603	0.967	0.965	0.966	0.935
	People who influence my behavior think that I should use ChatGPT to study	SI2	3.500	0.7569	0.986			
	People whose opinions I value prefer that I use ChatGPT to study	SI3	3.475	0.7428	0.948			
Trust in ChatGPT	ChatGPT is honest and truthful	TIC1	3.633	0.6459	0.950	0.952	0.953	0.874
	ChatGPT is capable of addressing my issues	TIC2	3.628	0.6309	0.953			
	ChatGPT's response and advice can meet my expectations	TIC3	3.571	0.6671	0.939			
	I trust the suggestions and decisions provided by ChatGPT	TIC4	3.546	0.6693	0.896			

Note(s): N = 392; M: Mean; S.D.: Standard deviation; λ: Outer loadings; α: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted
Source(s): The author's elaborations based on the research data

Table 2. Scale items and convergent validity analysis

the AVE values exceeded 0.5 for all constructs (Fornell and Larcker, 1981). Furthermore, the factor loadings on their respective constructs were greater than 0.7 (Fornell and Larcker, 1981). These findings collectively indicate that the measurement model exhibits acceptable levels of internal consistency, reliability, and convergent validity.

4.2 Structural model

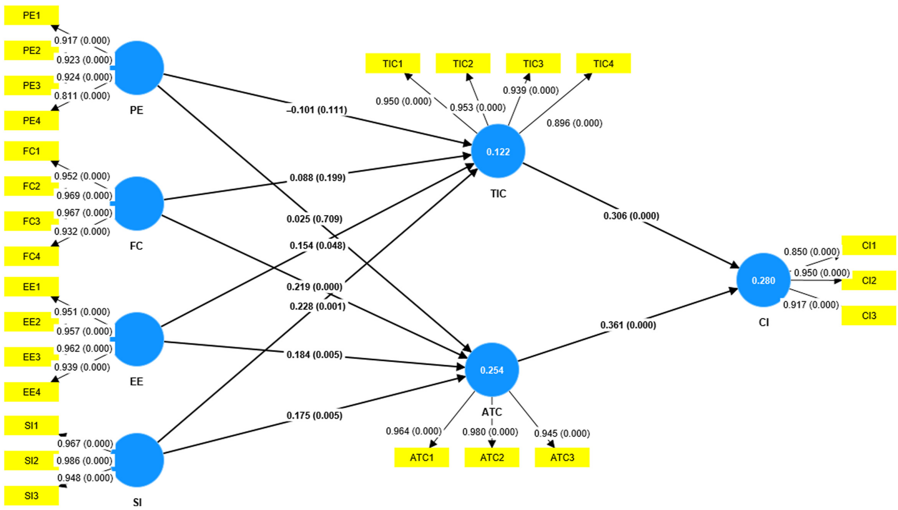
Table 3 and Figure 2 presented the result of unstandardized estimates of the research model. Analysis results show that performance expectancy did not significantly impact trust in ChatGPT ($p = 0.111 > 0.05$) or attitude towards ChatGPT ($p = 0.709 > 0.05$), contrary to our expectations. Thus, H1a and H1b were not supported. However, effort expectancy was found to have a positive and significant impact on trust in ChatGPT ($B = 0.154$, $p = 0.048$) as well as attitude towards ChatGPT ($B = 0.184$, $p = 0.005$), which supported H2a and H2b. Similarly, social influence also positively and significantly affects trust in ChatGPT ($B = 0.228$, $p = 0.001$) and attitude towards ChatGPT ($B = 0.175$, $p = 0.005$), supporting H3a, and H3b. Noticeably, facilitating conditions were found to significantly affect attitude towards ChatGPT ($B = 0.219$, $p = 0.000$), but not affect trust in ChatGPT ($p = 0.199 > 0.05$). Therefore, H4a was not supported and H4b was supported. Furthermore, the study found that students' intention to continue using ChatGPT was both positively and significantly influenced by trust in ChatGPT ($B = 0.306$, $p = 0.000$) and attitude towards ChatGPT ($B = 0.361$, $p = 0.000$), thus lending supporting H5 *and* H6.

The outcomes of indirect effects have been presented in Table 4. These findings demonstrate that social influence indirectly affected continuance usage intention through trust in ChatGPT ($B = 0.070$, $p = 0.007$) and attitude towards ChatGPT ($B = 0.063$, $p = 0.018$). Results also demonstrated that effort expectancy had indirect effects on continuance usage intention via attitude towards ChatGPT ($B = 0.067$, $p = 0.013$), but not via trust in ChatGPT ($p = 0.066 > 0.05$). Similarly, the findings indicated that attitude towards ChatGPT mediates the relationship between facilitating conditions and continuance usage intention ($B = 0.079$, $p = 0.001$), while trust in ChatGPT does not ($p = 0.220 > 0.05$).

Hypotheses	Paths			*B*	*p*-value	Supported [Yes/No]
H1a	Performance expectancy	→	Attitude toward ChatGPT	0.025	0.709	No
H1b	Performance expectancy	→	Trust in ChatGPT	−0.101	0.111	No
H2a	Effort expectancy	→	Attitude toward ChatGPT	0.184^{**}	0.005	Yes
H2b	Effort expectancy	→	Trust in ChatGPT	0.154^{*}	0.048	Yes
H3a	Social influence	→	Attitude toward ChatGPT	0.175^{**}	0.005	Yes
H3b	Social influence	→	Trust in ChatGPT	0.228^{**}	0.001	Yes
H4a	Facilitating conditions	→	Attitude toward ChatGPT	0.219^{***}	0.000	Yes
H4b	Facilitating conditions	→	Trust in ChatGPT	0.088	0.199	No
H5	Attitude toward ChatGPT	→	Continuance usage intention	0.361^{***}	0.000	Yes
H6	Trust in ChatGPT	→	Continuance usage intention	0.306^{***}	0.000	Yes

Note(s): $N = 392$; $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$
Source(s): The author's elaborations based on the research data

Table 3.
Hypotheses test results



Source(s): Figure based on the research data

Figure 2. Structural model results

Mediation regression coefficient paths			Indirect effects	S.D.	p-value	95% CIs LL	95% CIs UL
Performance expectancy	→ Trust in ChatGPT	→ Continuance usage intention	−0.031	0.020	0.128	−0.073	0.006
Performance expectancy	→ Attitude toward ChatGPT	→ Continuance usage intention	0.009	0.024	0.713	−0.039	0.054
Effort expectancy	→ Trust in ChatGPT	→ Continuance usage intention	0.047	0.026	0.066	0.003	0.105
Effort expectancy	→ Attitude toward ChatGPT	→ Continuance usage intention	0.067*	0.027	0.013	0.021	0.126
Social influence	→ Trust in ChatGPT	→ Continuance usage intention	0.070**	0.026	0.007	0.026	0.129
Social influence	→ Attitude toward ChatGPT	→ Continuance usage intention	0.063*	0.027	0.018	0.017	0.126
Facilitating conditions	→ Trust in ChatGPT	→ Continuance usage intention	0.027	0.022	0.220	−0.011	0.073
Facilitating conditions	→ Attitude toward ChatGPT	→ Continuance usage intention	0.079**	0.024	0.001	0.040	0.131

Note(s): $N = 392$. *$p < 0.05$. **$p < 0.01$; S.D.: Standard deviation; CIs: Confidence intervals; LL: Low limit; UL: Upper limit
Source(s): The author's elaborations based on the research data

Table 4. The result of indirect effects

5. Discussion

This study has employed the SOR model to investigate how UTAUT factors (such as performance expectancy, facilitating conditions, effort expectancy, and social influence) influence the cognitive responses of students (e.g., trust in ChatGPT and attitude towards ChatGPT), subsequently shaping their behavioral outcomes (e.g., the intention to continue using ChatGPT for study).

Firstly, the study postulated and empirically indicated that effort expectancy and social influence played an important role in stimulating students' cognitive organisms, such as trust in ChatGPT and attitude towards ChatGPT. These findings were in line with previous studies (Balakrishnan *et al.*, 2022; Kasilingam, 2020). It suggests that when students find their engagement with this AI tool to be straightforward and devoid of unnecessary complexities, it results in the stimulation of cognitive processes, particularly in building trust and forming favorable attitudes. In addition, this study indicates that when students are influenced positively by feedback or endorsements from their peers regarding ChatGPT, it becomes a potent catalyst in stimulating their cognitive responses. It reinforces the idea that interpersonal influence and recommendations have a crucial role in the development of trust and attitudes towards technology.

Secondly, although this study found that facilitating conditions did not affect students' trust in ChatGPT, it was the variable that most significantly affected their attitude towards ChatGPT. The findings suggest that despite these facilitating conditions, students' trust in ChatGPT remains relatively unaffected. In other words, the presence of supportive elements does not significantly enhance students' trust in technology. Even though facilitating conditions strongly influence students' attitudes towards ChatGPT. This suggests that students are highly receptive to the overall environment and resources available for using this technology, which, in turn, significantly shapes their attitudes (Balakrishnan *et al.*, 2022).

Thirdly, contrary to our expectations and previous studies, this study discovered that students' expectations of ChatGPT's performance did not have a significant impact on either their trust in the technology or their overall attitudes towards it. This finding is quite intriguing, as it challenges both the expectations of the researchers and the trends observed in previous studies. This unexpected outcome suggests a complex and multifaceted relationship between students and ChatGPT. While performance expectancy is often seen as a pivotal driver of trust and attitude in technology acceptance models, this study implies that in the specific context of ChatGPT use among students, other factors might be more influential in shaping their trust and attitudes.

Finally, this study provided empirical evidence that cognitive organisms, including trust in ChatGPT and attitude towards ChatGPT, can inspire students' behavioral responses (e.g., continuance usage intentions of ChatGPT for study). This finding was consistent with prior studies (Cheng *et al.*, 2022; Balakrishnan *et al.*, 2022; Kasilingam, 2020). It underscores the profound interplay between cognitive processes and subsequent actions. It implies that how students think and feel about ChatGPT, in terms of trust and attitude, significantly impacts their practical decisions regarding its continued usage for study.

6. Implications of the study

This study contributes significantly to the existing body of research by addressing a notable gap in the literature related to the adoption and continued usage of ChatGPT in educational settings. While prior research has recognized the importance of understanding the initial acceptance and adoption of ChatGPT in educational contexts, there has been a relative scarcity of studies delving into users' intentions to persist in using ChatGPT for learning purposes (Duong *et al.*, 2023b). The novelty of this study lies in its explicit focus on investigating students' continuance intentions to use ChatGPT by employing the well-established stimulus–organism–response (SOR) model. By extending the analysis beyond initial acceptance, the research provides valuable insights into the factors that influence the sustained utilization of ChatGPT in an educational environment. Ultimately, the findings of this study could have important implications for the design and implementation of ChatGPT in educational contexts, helping to inform future research and practice in this area.

First, the finding about the important role of effort expectancy in building students' trust in ChatGPT and attitude towards ChatGPT holds valuable practical implications for educators, developers, and educational institutions. Designing AI-driven educational tools with a strong emphasis on user-friendliness and an intuitive interface is imperative. Effort expectancy suggests that when these tools are easy to use and offer a seamless experience, they enhance students' trust and foster positive attitudes. Consequently, by prioritizing user-friendliness, comprehensive support, and continuous improvement based on user feedback, educational institutions and developers can significantly enhance the integration of such technologies into the learning process, ensuring a more effective and engaging educational experience for students.

Second, this study underscores the significant role of social influence in shaping students' trust and attitudes towards educational technology like ChatGPT. Thus, to harness this insight effectively, it is essential to recognize the power of peer recommendations and interactions in shaping students' perceptions. Educators can strategically facilitate positive peer-to-peer discussions and experiences regarding ChatGPT. This may involve creating platforms for students to share success stories, insights, and best practices with the technology, influencing their peers positively. Additionally, educators and institutions should consider integrating peer mentoring programs where experienced students, who have successfully used ChatGPT, guide and support their peers in maximizing the benefits of the technology. This peer-led approach can significantly boost social influence and trust in ChatGPT, as students tend to value advice and feedback from their fellow students.

Third, the finding that facilitating conditions positively enhances students' attitudes towards ChatGPT offers valuable practical implications for educators and technology developers. Educational institutions should invest in comprehensive training programs and readily accessible technical support, offering students the knowledge and assistance required to navigate and utilize ChatGPT effectively. This not only enhances students' confidence in their ability to use technology but also positively influences their attitudes. Furthermore, technology developers should recognize that creating a seamless and supportive ecosystem for using ChatGPT is crucial. Establishing feedback mechanisms where students can provide input, suggestions, and report issues contributes to the continuous improvement of the technology, enhancing students' attitudes and trust.

Finally, the finding that trust in ChatGPT and attitude towards ChatGPT can inspire students' intentions to continue using it for study holds profound practical implications for educators, institutions, and developers. It implies that a focus on building and maintaining students' trust through transparent and reliable interactions with technology is crucial. Ensuring that ChatGPT consistently delivers accurate and valuable support reinforces trust, encouraging students to see it as a dependable learning companion. Also, fostering a favorable attitude towards ChatGPT is equally important. This can be achieved by actively integrating ChatGPT into the curriculum, highlighting its relevance to the academic journey, and promoting its value in enhancing the learning process. When students perceive ChatGPT as an asset that positively contributes to their education, their attitudes become more favorable, influencing their intentions to continue using it.

7. Limitations and avenues for further research

While our research makes a substantial contribution to the understanding of how higher education students employ ChatGPT, it is crucial to acknowledge certain limitations that warrant further investigation. First and foremost, it's worth noting that the proposed model has been exclusively evaluated within the context of Vietnam. Expanding this research to various countries, particularly in cross-cultural scenarios, could potentially yield more captivating insights into this burgeoning field. Second, this study only focuses on students' intentions to embrace ChatGPT, while there is a gap between intention and behavior (Ajzen, 2020; Nguyen *et al.*, 2019). Therefore, further studies could expand the proposed model to investigate students' actual behavior toward utilizing ChatGPT for learning. Thirdly, it's essential to recognize that our study was confined to undergraduate students, which might limit the extent to which our findings can be applied across broader populations. To enhance the relevance and applicability of our conclusions, future research should encompass data collection from diverse academic disciplines and educational levels, including master's and Ph.D. students.

References

Ajzen, I. (2020), "The theory of planned behavior: frequently asked questions", *Human Behavior and Emerging Technologies*, Vol. 2 No. 4, pp. 314-324, doi: 10.1002/hbe2.195.

Alkhowaiter, W.A. (2022), "Use and behavioural intention of m-payment in GCC countries: extending meta-UTAUT with trust and Islamic religiosity", *Journal of Innovation & Knowledge*, Vol. 7 No. 4, 100240, doi: 10.1016/j.jik.2022.100240.

Anders, B.A. (2023), "Is using ChatGPT cheating, plagiarism, both, neither, or forward thinking?", *Patterns*, Vol. 4 No. 3, 100694, doi: 10.1016/j.patter.2023.100694.

Anega, N.M. and Alemu, B. (2023), "The effect of rural roads on consumption in Ethiopia", *Journal of Economics and Development*, Vol. 25 No. 3, pp. 186-204, doi: 10.1108/jed-10-2022-0213.

Ashfaq, M., Yun, J., Yu, S. and Loureiro, S.M.C. (2020), "I, Chatbot: modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents", *Telematics and Informatics*, Vol. 54, 101473, doi: 10.1016/j.tele.2020.101473.

Balakrishnan, J. and Dwivedi, Y.K. (2021), "Conversational commerce: entering the next stage of AI-powered digital assistants", *Annals of Operations Research*, Vol. 333 Nos 2-3, pp. 653-687, doi: 10.1007/s10479-021-04049-5.

Balakrishnan, J., Abed, S.S. and Jones, P. (2022), "The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services?", *Technological Forecasting and Social Change*, Vol. 180, 121692, doi: 10.1016/j.techfore.2022.121692.

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

Bin-Nashwan, S.A., Sadallah, M. and Bouteraa, M. (2023), "Use of ChatGPT in academia: academic integrity hangs in the balance", *Technology in Society*, Vol. 75, 102370, doi: 10.1016/j.techsoc.2023.102370.

Chakraborty, D., Singu, H.B., Kar, A.K. and Biswas, W. (2023), "From fear to faith in the adoption of medicine delivery application: an integration of SOR framework and IRT theory", *Journal of Business Research*, Vol. 166, 114140, doi: 10.1016/j.jbusres.2023.114140.

Chaouali, W., Ben Yahia, I. and Souiden, N. (2016), "The interplay of counter-conformity motivation, social influence, and trust in customers' intention to adopt Internet banking services: the case of an emerging country", *Journal of Retailing and Consumer Services*, Vol. 28, pp. 209-218, doi: 10.1016/j.jretconser.2015.10.007.

Chen, L., Jia, J. and Wu, C. (2023), "Factors influencing the behavioral intention to use contactless financial services in the banking industry: an application and extension of UTAUT model", *Frontiers in Psychology*, Vol. 14, 1096709, doi: 10.3389/fpsyg.2023.1096709.

Cheng, X., Zhang, X., Cohen, J. and Mou, J. (2022), "Human vs. AI: understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms", *Information Processing & Management*, Vol. 59 No. 3, 102940, doi: 10.1016/j.ipm.2022.102940.

Cokins, G., Oncioiu, I., Türkeş, M.C., Topor, D.I., Căpuşneanu, S., Paştiu, C.A., Deliu, D. and Solovăstru, A.N. (2020), "Intention to use accounting platforms in Romania: a quantitative study on sustainability and social influence", *Sustainability*, Vol. 12 No. 15, p. 6127, doi: 10.3390/su12156127.

Dağhan, G. and Akkoyunlu, B. (2016), "Modeling the continuance usage intention of online learning environments", *Computers in Human Behavior*, Vol. 60, pp. 198-211, doi: 10.1016/j.chb.2016.02.066.

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

Duong, C.D. (2022), "Cultural values and energy-saving attitude-intention-behavior linkages among urban residents: a serial multiple mediation analysis based on stimulus-organism-response model", *Management of Environmental Quality: An International Journal*, Vol. 34 No. 3, pp. 647-669, doi: 10.1108/meq-09-2022-0258.

Duong, C.D., Bui, D.T., Pham, H.T., Vu, A.T. and Nguyen, V.H. (2023a), "How effort expectancy and performance expectancy interact to trigger higher education students' uses of ChatGPT for learning", *Interactive Technology and Smart Education*, Vol. ahead-of-print No. ahead-of-print, pp. 1-25, doi: 10.1108/itse-05-2023-0096.

Duong, C.D., Vu, T.N. and Ngo, T.V.N. (2023b), "Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: a serial multiple mediation model with knowledge sharing as a moderator", *The International Journal of Management Education*, Vol. 21 No. 3, 100883, doi: 10.1016/j.ijme.2023.100883.

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A., Clement, M. and Williams, M.D. (2017), "Re-examining the unified theory of acceptance and use of technology (UTAUT): towards a revised theoretical model", *Information Systems Frontiers*, Vol. 21 No. 3, pp. 719-734, doi: 10.1007/s10796-017-9774-y.

Dwivedi, Y.K., Pandey, N., Currie, W. and Micu, A. (2023), "Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda", *International Journal of Contemporary Hospitality Management*, Vol. 36 No. 1, pp. 1-12, doi: 10.1108/ijchm-05-2023-0686.

Følstad, A., Nordheim, C.B. and Bjørkli, C.A. (2018), "What makes users trust a chatbot for customer service? An exploratory interview study", in Bodrunova, S. (Ed.), *Internet Science, INSCI 2018, Lecture Notes in Computer Science*, Springer, Cham, Vol. 11193, doi: 10.1007/978-3-030-01437-7_16.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50, doi: 10.2307/3151312.

Foroughi, B., Sitthisirinan, S., Iranmanesh, M., Nikbin, D. and Ghobakhloo, M. (2023), "Determinants of travel apps continuance usage intention: extension of technology continuance theory", *Current Issues in Tourism*, Vol. 27 No. 4, pp. 1-17, doi: 10.1080/13683500.2023.2169109.

Gao, L. and Waechter, K.A. (2015), "Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation", *Information Systems Frontiers*, Vol. 19 No. 3, pp. 525-548, doi: 10.1007/s10796-015-9611-0.

Gkinko, L. and Elbanna, A. (2023), "Designing trust: the formation of employees' trust in conversational AI in the digital workplace", *Journal of Business Research*, Vol. 158, 113707, doi: 10.1016/j.jbusres.2023.113707.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2010), *Multivariate Data Analysis*, Pearson Prentice Hall, Upper Saddle River, NJ.

Hair Jr, J.F. (2020), "Next-generation prediction metrics for composite-based PLS-SEM", *Industrial Management and Data Systems*, Vol. 121 No. 1, pp. 5-11, doi: 10.1108/imds-08-2020-0505.

Harman, H.H. (1976), *Modern Factor Analysis*, 3rd ed., University of Chicago Press, Chicago.

Hoi, V.N. (2020), “Understanding higher education learners’ acceptance and use of mobile devices for language learning: a Rasch-based path modeling approach”, *Computers & Education*, Vol. 146, 103761, doi: 10.1016/j.compedu.2019.103761.

Hyun Baek, T. and Kim, M. (2023), “Is ChatGPT scary good? How user motivations affect creepiness and trust in generative artificial intelligence”, *Telematics and Informatics*, Vol. 83, 102030, doi: 10.1016/j.tele.2023.102030.

Kasilingam, D.L. (2020), “Understanding the attitude and intention to use smartphone chatbots for shopping”, *Technology in Society*, Vol. 62, 101280, doi: 10.1016/j.techsoc.2020.101280.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Kuhn, J. and Kasneci, G. (2023), “ChatGPT for good? On opportunities and challenges of large language models for education”, *Learning and Individual Differences*, Vol. 103, 102274, doi: 10.1016/j.lindif.2023.102274.

Lai, C.Y., Cheung, K.Y. and Chee Seng, C. (2023), “Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: an extension of the technology acceptance model”, *Computers and Education: Artificial Intelligence*, Vol. 5, 100178, doi: 10.1016/j.caeai.2023.100178.

Leong, T.K., Chiek, A.N. and Lim, C.W. (2021), “A modified Utaut in the context of M-payment usage intention in Malaysia”, *Journal of Applied Structural Equation Modeling*, Vol. 5 No. 1, pp. 39-60, doi: 10.47263/jasem.5(1)05.

Lim, W.M., Gunasekara, A., Pallant, J.L., Pallant, J.I. and Pechenkina, E. (2023), “Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators”, *The International Journal of Management Education*, Vol. 21 No. 2, 100790, doi: 10.1016/j.ijme.2023.100790.

Liu, C. and Huang, X. (2023), “Does the selection of virtual reality video matter? A laboratory experimental study of the influences of arousal”, *Journal of Hospitality and Tourism Management*, Vol. 54, pp. 152-165, doi: 10.1016/j.jhtm.2022.12.002.

Manser Payne, E., Peltier, J.W. and Barger, V.A. (2018), “Mobile banking and AI-enabled mobile banking”, *Journal of Research in Interactive Marketing*, Vol. 12 No. 3, pp. 328-346, doi: 10.1108/jrim-07-2018-0087.

Mehrabian, A. and Russell, J.A. (1974), *An Approach to Environmental Psychology*, MIT Press, Cambridge, MA.

Menon, D. and Shilpa, K. (2023), “‘Chatting with ChatGPT’: analyzing the factors influencing users’ intention to use the open AI’s ChatGPT using the UTAUT model”, *Heliyon*, Vol. 9 No. 11, e20962, doi: 10.1016/j.heliyon.2023.e20962.

Nguyen, H.V., Nguyen, C.H. and Hoang, T.T.B. (2019), “Green consumption: closing the intention-behavior gap”, *Sustainable Development*, Vol. 27 No. 1, pp. 118-129, doi: 10.1002/sd.1875.

Nikolopoulou, K., Gialamas, V. and Lavidas, K. (2021), “Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers’ intention to use mobile internet”, *Computers and Education Open*, Vol. 2, 100041, doi: 10.1016/j.caeo.2021.100041.

Park, J., Ahn, J., Thavisay, T. and Ren, T. (2019), “Examining the role of anxiety and social influence in multi-benefits of mobile payment service”, *Journal of Retailing and Consumer Services*, Vol. 47, pp. 140-149, doi: 10.1016/j.jretconser.2018.11.015.

Qi, X., Zhu, Z. and Wu, B. (2023), “The promise and peril of ChatGPT in geriatric nursing education: what we know and do not know”, *Aging and Health Research*, Vol. 3 No. 2, 100136, doi: 10.1016/j.ahr.2023.100136.

Sung, E., Bae, S., Han, D.-I.D. and Kwon, O. (2021), “Consumer engagement via interactive artificial intelligence and mixed reality”, *International Journal of Information Management*, Vol. 60, 102382, doi: 10.1016/j.ijinfomgt.2021.102382.

Thi Tuyet Mai, N. (2019), "An investigation into the relationship between materialism and green purchase behavior in Vietnam and Taiwan", *Journal of Economics and Development*, Vol. 21 No. 2, pp. 247-258, doi: 10.1108/jed-10-2019-0044.

Tiwari, C.K., Bhat, M.A., Khan, S.T., Subramaniam, R. and Khan, M.A.I. (2023), "What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT", *Interactive Technology and Smart Education*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/itse-04-2023-0061.

Upadhyay, N. and Kamble, A. (2023), "Examining Indian consumer pro-environment purchase intention of electric vehicles: perspective of stimulus-organism-response", *Technological Forecasting and Social Change*, Vol. 189, 122344, doi: 10.1016/j.techfore.2023.122344.

Venkatesh, V. (2021), "Adoption and use of AI tools: a research agenda grounded in UTAUT", *Annals of Operations Research*, Vol. 308 Nos 1-2, pp. 641-652, doi: 10.1007/s10479-020-03918-9.

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, p. 425, doi: 10.2307/30036540.

Verma, P. and Sinha, N. (2018), "Integrating perceived economic wellbeing to technology acceptance model: the case of mobile based agricultural extension service", *Technological Forecasting and Social Change*, Vol. 126, pp. 207-216, doi: 10.1016/j.techfore.2017.08.013.

Wong, I.A., Lian, Q.L. and Sun, D. (2023), "Autonomous travel decision-making: an early glimpse into ChatGPT and generative AI", *Journal of Hospitality and Tourism Management*, Vol. 56, pp. 253-263, doi: 10.1016/j.jhtm.2023.06.022.

Wood, W. (2000), "Attitude change: persuasion and social influence", *Annual Review of Psychology*, Vol. 51 No. 1, pp. 539-570, doi: 10.1146/annurev.psych.51.1.539.

Wu, B. and Chen, X. (2017), "Continuance intention to use MOOCs: integrating the technology acceptance model (TAM) and task technology fit (TTF) model", *Computers in Human Behavior*, Vol. 67, pp. 221-232, doi: 10.1016/j.chb.2016.10.028.

Xie, Y., Zhu, K., Zhou, P. and Liang, C. (2023), "How does anthropomorphism improve human-AI interaction satisfaction: a dual-path model", *Computers in Human Behavior*, Vol. 148, 107878, doi: 10.1016/j.chb.2023.107878.

Xu, X., Yao, Z. and Teo, T.S.H. (2020), "Moral obligation in online social interaction: clicking the "like" button", *Information & Management*, Vol. 57 No. 7, 103249, doi: 10.1016/j.im.2019.103249.

Yan, H. and Yang, Z. (2015), "Examining mobile payment user adoption from the perspective of trust", *International Journal of u- and e-Service, Science and Technology*, Vol. 8 No. 1, pp. 117-130, doi: 10.14257/ijunesst.2015.8.1.11.

Zhu, B., Kowatthanakul, S. and Satanasavapak, P. (2019), "Generation Y consumer online repurchase intention in Bangkok", *International Journal of Retail & Distribution Management*, Vol. 48 No. 1, pp. 53-69, doi: 10.1108/ijrdm-04-2018-0071.

Corresponding author
Cong Doanh Duong can be contacted at: doanhdc@neu.edu.vn