Humanities and Social Sciences Letters
2026 Vol. 14, No. 4, pp. 645-665
ISSN(e): 2312-4318
ISSN(p): 2312-5659
DOI: 10.18488/73.v14i4.5356
© 2026 Conscientia Beam. All Rights Reserved.

Factors influencing ChatGPT adoption in higher education: The pivotal role of AI awareness

Dang Thi Bao Tram[1]
Bui Huy Khoi[2+]
To Xuan Quynh[3]
Phan Thi My Ngan[4]

[1,2,3,4]*Industrial University of Ho Chi Minh City, Vietnam.*
[1]*Email: dangthibaotram@iuh.edu.vn*
[2]*Email: buihuykhoi@iuh.edu.vn*
[3]*Email: quynhtx26831@pgr.iuh.edu.vn*
[4]*Email: nganptm26451@pgr.iuh.edu.vn*



(+ Corresponding author)

Article History
Received: 22 June 2026
Revised: 17 August 2026
Accepted: 4 September 2026
Published: 11 November 2026

Keywords
AI awareness
Behavioral intention
ChatGPT
Higher education
PLS-SEM
Trust in AI.

ABSTRACT

This study investigates the factors influencing university students' adoption of ChatGPT for learning in Ho Chi Minh City, Vietnam, with particular emphasis on the role of AI awareness in shaping technology acceptance. Drawing on the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study develops a framework linking AI awareness, perceived usefulness, perceived ease of use, trust, and behavioral intention to use ChatGPT. A mixed-methods approach was employed. First, a bibliometric review of 1,362 Scopus-indexed publications was conducted to identify major research trends and knowledge gaps concerning ChatGPT in higher education. Second, survey data collected from 300 university students were analyzed using partial least squares structural equation modeling (PLS-SEM) to test the proposed relationships. The findings reveal that AI awareness positively enhances students' perceptions of usefulness, ease of use, and trust in ChatGPT. In turn, perceived usefulness, perceived ease of use, and trust significantly contribute to students' behavioral intention to adopt ChatGPT for academic purposes. Among these factors, trust emerges as the most influential mechanism linking AI awareness to adoption intention, highlighting the importance of confidence in AI technologies within educational settings. The study provides practical implications for higher education institutions by emphasizing the need to strengthen AI literacy, promote transparent and responsible AI use, and develop training initiatives that increase students' confidence and readiness to integrate generative AI tools into learning activities.

Contribution/Originality: This study contributes to the existing literature by integrating TAM, TPB, and UTAUT within the context of Vietnamese higher education. It uses a two-stage methodology combining bibliographic analysis with PLS-SEM. The paper's primary contribution is finding that trust is the most potent mediator between AI awareness and adoption intention.

1. INTRODUCTION

Higher education is changing fast as artificial intelligence, especially tools like ChatGPT, gets woven into everyday academic life (Fütterer et al., 2023; Memarian & Doleck, 2023). These systems aren't just flashy tech; they give students real-time feedback, help with writing, and sort through complicated information with ease (Baidoo-Anu & Owusu Ansah, 2023; Farrokhnia, Banihashem, Noroozi, & Wals, 2024; Tlili et al., 2023). There's solid evidence that using ChatGPT can boost students' motivation and get them thinking more deeply (Caratiquit & Caratiquit,

© 2026 Conscientia Beam. All Rights Reserved.

2023; Lo, Hew, & Jong, 2024). But there's a flipside: its rapid spread has led to new problems, such as cheating, spreading false information, and people leaning on it too much (Ali et al., 2024; Jang, 2024; Tanvir, Islam, Sezan, Sanad, & Ataur, 2023). Even with these challenges, most research still leans on old models like the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), which mainly look at direct effects.

But the conversation has two significant gaps. First, we are missing deeper models that examine the psychology behind why people accept or reject AI, such as how awareness of AI (AIA) lays the groundwork for whether students trust it (TRU), find it useful (PU), or consider it easy to use (PEOU), eventually shaping their behavioral intention to use it (BI) (Shahzad, Xu, & Javed, 2024). Second, there is a real imbalance in research: most of what we know comes from Western countries, especially the US and UK. There is hardly any empirical data from Asian settings, and even less from Vietnam, despite the country's significant digital push in higher education. This study steps in to fill those gaps. It focuses on what drives university students in Ho Chi Minh City to use ChatGPT, drawing on a framework that blends the Theory of Planned Behavior (Ajzen, 1991), TAM, and UTAUT. Ho Chi Minh City is a digital trailblazer in Vietnam, so the findings should say a great deal about how new technology fits into Asian higher education settings.

To address these research objectives, the study explores the following research questions:

- RQ1: How does AI Awareness (AIA) influence students' perceived usefulness, perceived ease of use, and trust in ChatGPT?
- RQ2: To what extent do trust, perceived usefulness, and perceived ease of use mediate the relationship between AI Awareness (AIA) and students' behavioral intention to use ChatGPT for learning?

The remainder of this paper is structured as follows:

- Section 2 provides a bibliometric review, outlines the theoretical framework, and develops the research hypotheses.
- Section 3 describes the mixed-methods methodology, including sampling and measurement scales.
- Section 4 presents the results of the PLS-SEM analysis and discusses the findings in relation to existing literature.
- Section 5 concludes the study by summarizing the key results, presenting managerial implications, and suggesting directions for future research.



Figure 1. Main information about data collection.

© 2026 Conscientia Beam. All Rights Reserved.

2. BIBLIOMETRIC REVIEW, THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

2.1. Bibliometric Analysis

Figure 1 illustrates the main information regarding the bibliographic data collection, summarizing the key metrics of the dataset retrieved from Biblioshiny for this study. Research on Artificial Intelligence and ChatGPT in higher education is taking off rapidly. When examining the numbers, this is clear. A search of the Scopus database for "ChatGPT" and "higher education" returned 1,362 publications from 535 sources, all published between 2023 and 2026 (including "online first" articles already scheduled for 2026). Each year, the field has grown by nearly 29%. That is quite remarkable. On average, each paper receives approximately 16 citations, which shows that researchers are paying close attention to what is being published. Most of these studies are still recent, averaging just over one year old. Thus, we are looking at a field that is still finding its footing while constantly shifting and expanding. Collaboration is common, too. Most papers have about 3 or 4 authors, although 224, to be exact, are from solo researchers. International teamwork is not uncommon either: over a quarter of the papers were co-written by authors from different countries. There is room to grow, but the energy is evident. If we examine the details, there are almost 60,000 references and nearly 3,000 unique keywords. The knowledge base is growing rapidly. In short, research on AI and ChatGPT in higher education is not merely active; it is booming, and collaboration is at its heart.

The bibliometric results presented in Figure 2 show that the United States, China, the United Kingdom, and Australia are the most influential countries in the field of AI and ChatGPT in higher education, as evidenced by their substantially higher citation counts than those of other countries.

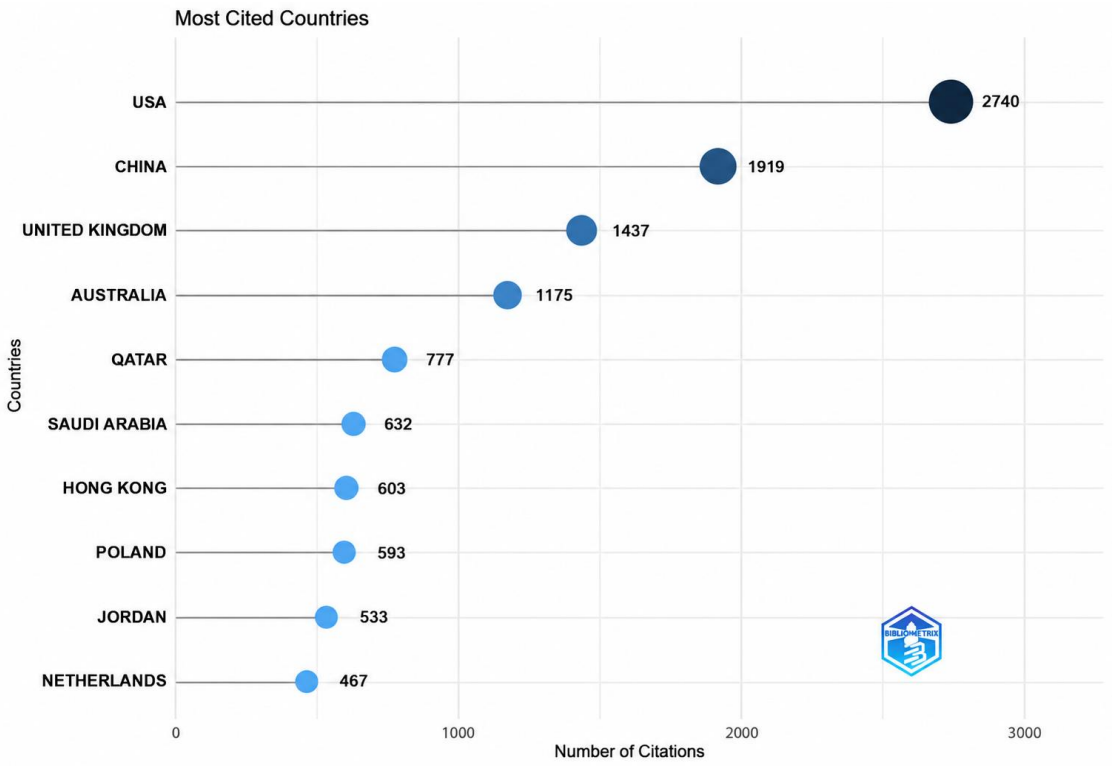


Figure 2. Most Cited Countries.

Furthermore, Figure 3 illustrates a wordcloud of these most frequent terms, visually highlighting the core research themes that dominate the current academic discourse. The prominence of these keywords suggests that recent research has focused not only on the educational benefits of ChatGPT and generative AI but also on challenges related to academic integrity, ethical concerns, and the evolving role of AI in supporting student learning.

© 2026 Conscientia Beam. All Rights Reserved.

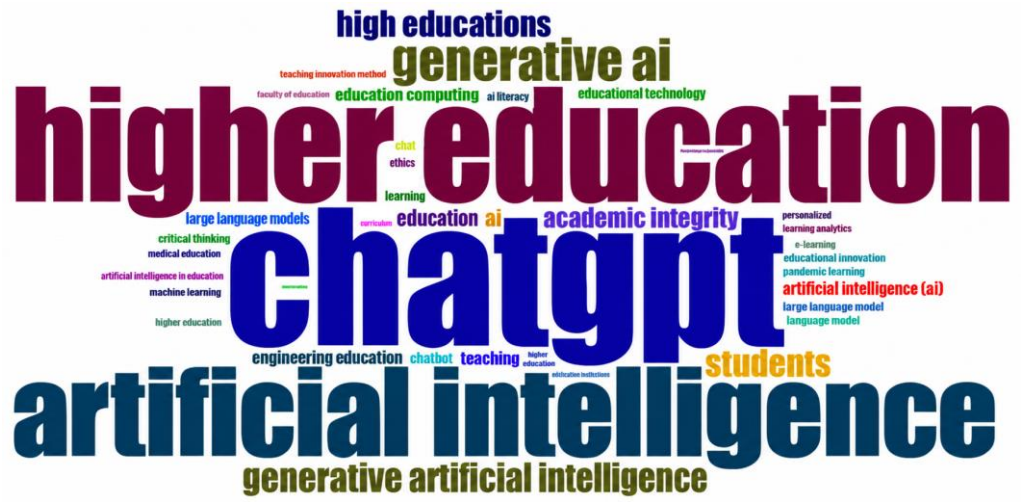


Figure 3. Word cloud.

China has played a significant role in this research field, but few other Asian countries appear among the top contributors. Most of the work still comes from Western countries. This gap shows that there is a real need for more research from Asia, especially to examine what shapes the acceptance, adoption, and management of AI in the region's universities. More research from Asian perspectives would help schools as they determine how to use digital tools, ensuring that their plans fit the culture, teaching styles, and realities they encounter every day.

2.2. Theoretical Framework

2.2.1. Artificial Intelligence (AI)

Artificial intelligence, or AI, is a part of computer science that focuses on building systems that act like humans. These systems can understand, learn, and make decisions. Technologies like natural language processing and machine learning help machines manage tasks that usually require human intelligence, including reasoning, planning, and even creativity. Researchers often define AI as enabling machines to perform work that normally requires a thinking person.

2.2.2. ChatGPT

OpenAI built ChatGPT on the Generative Pre-trained Transformer (GPT) architecture. This AI language model understands and generates text that feels remarkably human in all kinds of situations. GPT-based systems aren't just about clever conversation; they're changing the way people learn and teach (Sajja, Sermet, Cwiertny, & Demir, 2023). ChatGPT, which relies on the advanced GPT-3.5 framework, uses powerful Natural Language Processing (NLP) tools to give responses that fit the context. This is not just a step forward for NLP; it's a real turning point that's influencing everything from customer service and healthcare to, increasingly, education. In schools and universities, ChatGPT offers personalized support, providing practical advice tailored to a student's strengths, goals, and objectives, especially for academic writing and learning new languages (Baidoo-Anu & Owusu Ansah, 2023; Tlili et al., 2023).

2.2.3. Theory of Planned Behavior (TPB)

Ajzen's Theory of Planned Behavior (TPB) takes things a step further than the earlier Theory of Reasoned Action (TRA) by adding perceived behavioral control to the mix. TRA was good, but it struggled with behaviors affected by real-life obstacles or external limitations. That's where TPB comes in. According to this theory, three things drive a person's intention to act: their attitude toward the behavior, the social pressures they feel (what Ajzen calls the subjective norm), and their sense of how much control they have over taking action. Of all these factors, behavioral

© 2026 Conscientia Beam. All Rights Reserved.

intention predicts what people will actually do. Digging deeper, attitude is simply how you feel, positively or negatively, about doing something. Subjective norm is all about how much pressure you feel from the people who matter to you. Perceived behavioral control concerns whether you think the behavior is easy or difficult, based on the barriers and resources you believe you have. This framework helps explain why people sometimes plan to do something but are blocked by real-world limitations.

2.2.4. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the go-to theories for understanding why people accept and use new technology. At its core, TAM focuses on two main ideas: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is how much someone believes a technology will help them do their job better. PEOU is about how easy they think the technology is to use. Both shape how people feel about using the technology, whether they actually intend to use it, and whether they end up using it in practice. Interestingly, when people find a tool easy to use, they often see it as more useful, which means PEOU can indirectly influence PU.

2.2.5. Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) and his team developed the Unified Theory of Acceptance and Use of Technology (UTAUT) in 2003 to understand why people accept or reject modern technology. It is important in the field; researchers say it explains as much as 70% of what drives someone's intention to use new technology. That predictive power makes it one of the strongest models for understanding technology adoption. By identifying the main factors behind technology acceptance, UTAUT also helps organizations design better ways to encourage people who might otherwise hold back. The original model highlights four factors that really matter: performance expectancy, effort expectancy, social influence, and facilitating conditions. Later, Venkatesh, Thong, and Xu (2012) expanded the model to better capture how people behave as consumers. They called it UTAUT2, adding hedonic motivation, price value, and habit to the framework. These updates made the model even more flexible, allowing researchers and businesses to study technology adoption across a wider range of situations and with more precise measurements.

2.3. Hypothesis Development

2.3.1. AI Awareness (AIA)

When people use smart technologies like ChatGPT or Gemini, the way they view AI shapes what they expect from, and ultimately gain from, the experience. Al-Abdullatif (2023) points out that when people understand both the possibilities and the limitations of AI, they develop more realistic expectations. This usually leads to smoother, more satisfying interactions. There is also strong evidence that being aware of how AI works, what it does well, and where it falls short makes people view these tools as more useful (Shahzad et al., 2024). Once someone sees how AI can help in school, at work, or in daily life, they are more likely to view it as genuinely helpful (Niu & Mvondo, 2024). It is not just about being useful, either. AI awareness also shapes how easy people think these tools are to use. Shahzad et al. (2024) found that the more people know about how AI applications like ChatGPT function, the friendlier and less intimidating these tools seem. When you know your way around the features, everything feels more convenient. Trust is another important factor. Abdelkader (2023) and Shahzad et al. (2024) both argue that people who understand what AI can and cannot do, as well as the basics of how it handles data and security, tend to trust the technology more. People with high AI awareness judge these systems more realistically, which boosts confidence. However, trust is not automatic. If you want people to continue trusting AI, you cannot ignore privacy, data security, or the risk of misuse (Lai, Cheung, & Chan, 2023).

So, building on these ideas and previous research, here are the hypotheses:

H_1: AI Awareness (AIA) positively influences Perceived Usefulness (PU) among university students in Ho Chi Minh City.

© 2026 Conscientia Beam. All Rights Reserved.

H_4: AI Awareness (AIA) positively influences Perceived Ease of Use (PEOU) among university students in Ho Chi Minh City.

H_5: AI Awareness (AIA) positively influences Trust (TRU) among university students in Ho Chi Minh City.

2.3.2. Perceived Usefulness (PU)

Davis (1989) argued that people judge the value of an information system by how much they believe it helps them do their jobs better. If users see real benefits that help them reach their goals, they are more likely to view a technology positively. Plenty of research supports this view. Studies consistently show that when people believe a learning technology is useful- a concept often called perceived usefulness, or PU- they are more likely to use it and intend to continue using it. For example, Al-Emran, Arpaci, and Salloum (2020); Alshurideh, Al Kurdi, Salloum, Arpaci, and Al-Emran (2023) and Sewandono, Thoyib, Hadiwidjojo, and Rofiq (2023) all found that perceived usefulness plays a significant role in students' decisions to use mobile learning (M-learning) systems.

As educational technology advances, it has become increasingly important to understand what drives people to adopt new technology in learning environments. Perceived usefulness continues to emerge as a key factor, especially with AI-powered tools like ChatGPT (Gumbo, Halimani, & Diza, 2017; Khalid, 2014). When students feel that ChatGPT can help with academic work, tackle problems, or make it easier to find information, their willingness to use it increases considerably. Earlier studies underline this point: perceived usefulness strongly shapes whether people intend to use AI technology for education (Shahzad et al., 2024). Based on these arguments, the following hypothesis is proposed:

H_6: Perceived Usefulness (PU) positively influences university students' Behavioral Intention (BI) to use ChatGPT in Ho Chi Minh City.

2.3.3. Perceived Ease of Use (PEOU)

People are more likely to use AI tools like ChatGPT and Gemini when they feel easy to use and accessible. That's why perceived ease of use (PEOU) is such a big deal in determining whether people actually accept new technology (Gumbo et al., 2017). Na, Heo, Han, Shin, and Roh (2022) examined how students feel about ChatGPT and found that when students perceive the technology as straightforward, they are much more willing to use it in their studies. Jo (2025) pointed out how important it is for the design, including things like the user interface and overall experience, to make these tools feel easier to handle. There is more to it, though. de Andrés-Sánchez and Gené-Albesa (2023) showed that people find AI systems easier to use when those systems give answers that are accurate, make sense, and are tailored to what users actually need. Maheshwari (2024) took it further, saying that PEOU actually connects how people see these tools to whether they will use them. Basically, once people are more aware of and understand how the technology works, they see it as less intimidating, which makes them more open to trying it out. Almogren, Al-Rahmi, and Dahri (2024) examined how college students adopt ChatGPT and found that factors such as whether they enjoy using it, the quality of its answers, and even what their friends think all play a role. All in all, these studies paint a clearer picture of how and why people start using tools like ChatGPT, showing that it's not just about the technology itself; it's also about design, experience, and what's going on in people's lives. Based on the above arguments, the following hypothesis is proposed.

H_7: Perceived Ease of Use (PEOU) positively influences Behavioral Intention (BI) to use ChatGPT among university students in Ho Chi Minh City.

2.3.4. Trust (TRU)

Trust in artificial intelligence isn't just a buzzword; it's about whether people actually believe these systems are reliable, accurate, and secure when they give advice or offer help (Ofosu-Ampong, Acheampong, Kevor, & Amankwah-Sarfo, 2023). This sense of trust really matters, especially in places like schools, where tools like ChatGPT and Gemini

© 2026 Conscientia Beam. All Rights Reserved.

are becoming part of the learning experience. If students or teachers do not trust the information, or if the system feels unpredictable or unsafe, they simply won't use it. Reliability, accuracy, and transparency all contribute to this. Trust helps users feel comfortable enough to rely on AI, rather than merely trying it once and ignoring it. When these factors are missing, adoption slows down. That's why keeping these systems dependable and clear about how they work is so important, so everyone feels safe enough to engage with them and let AI become part of daily routines (Al-Momani, 2023; Shahzad et al., 2024). People usually stick with technology when they trust that it won't disappoint them, and that's how real adoption happens (Baek & Kim, 2023). Based on the above arguments, the following hypothesis is proposed.

H_6: Trust (TRU) positively influences Behavioral Intention (BI) to use ChatGPT among university students in Ho Chi Minh City.

2.3.5. Mediating Hypotheses

Looking at how Perceived Usefulness (PU) acts as a bridge between AI Awareness (AIA) and students actually using AI tech is pretty important, especially now that AI is showing up everywhere in education. Davis (1989) defined perceived usefulness back in 1989 as how much someone believes a modern technology will boost their performance. Basically, if students believe tools like ChatGPT really help them learn better, they're more likely to feel positive about AI and want to keep using it (Al-Emran, Mezhuyev, & Kamaludin, 2018; Lin & Yu, 2023; Rudolph, Tan, & Tan, 2023). However, before students perceive AI as useful, they need to understand what AI can and cannot do. Students who understand AI's strengths and limitations are better able to judge its actual value (Al-Abdullatif, 2023; Bilquise, Ibrahim, & Salhieh, 2024). Research keeps backing this up; Niu and Mvondo (2024) show that knowing more about AI makes people appreciate its usefulness more, which nudges them toward using it. This all lines up with the expanded TAM framework: perceived usefulness isn't just about what people think on the surface; it's shaped by how they understand the tech, and it's key in turning awareness into actual behavior (Venkatesh et al., 2003). Studies by Alshurideh et al. (2023) and Sewandono et al. (2023) also highlight PU as a major factor in adopting digital and AI-based learning tools. In short, perceived usefulness explains how awareness of AI translates into action: students choose tools like ChatGPT for academic purposes because they genuinely believe these tools will help them. Both theory and recent research support this (Davis, 1989; Shahzad et al., 2024; Venkatesh et al., 2003). Accordingly, the following mediating hypothesis is proposed.

H_{1-4}: Perceived Usefulness (PU) mediates the relationship between AI Awareness (AIA) and Behavioral Intention (BI) to use ChatGPT for learning among university students in Ho Chi Minh City.

Perceived Ease of Use (PEOU) really matters when it comes to technology adoption. Davis (1989) puts it simply: it refers to how much effort someone thinks they need to exert to use a new system. If students see a tool as easy to learn, intuitive, and user-friendly, they are much more likely to use it. Gumbo et al. (2017) point this out, and it is a reasonable conclusion. With AI tools like ChatGPT, this idea plays an even bigger role because users need to engage with the system in real time. Na et al. (2022) and Shahzad et al. (2024) both found that students who understand AI somewhat better perceive ChatGPT as easier to use, which encourages them to adopt it for their learning. UI and UX design matter, too. A clean interface, fast responses, and clear instructions all help students feel more confident and willing to use ChatGPT repeatedly (de Andrés-Sánchez & Gené-Albesa, 2023; Jo, 2025). From a theoretical perspective, this idea appears in both the Technology Acceptance Model (TAM) and Rogers, Singhal, and Quinlan (2014). If students begin with positive impressions of new technology, such as viewing AI as approachable, they are more likely to judge it as easy to use, which makes them want to continue using it. Other factors matter, too: when users notice that AI is transparent about how it works, provides accurate responses, or adapts to their needs, their perception that "this is easy" becomes even stronger (Limna, Kraiwanit, Jangjarat, Klayklung, & Chocksathaporn, 2023; Maheshwari, 2024; Shahzad et al., 2024). In the end, Perceived Ease of Use acts as the bridge linking students'

© 2026 Conscientia Beam. All Rights Reserved.

initial feelings about AI to whether they actually intend to use ChatGPT as a learning tool. Based on the arguments above, the following mediating hypothesis is proposed.

H_{2-5}: Perceived Ease of Use (PEOU) mediates the relationship between AI Awareness (AIA) and Behavioral Intention (BI) to use ChatGPT for learning among university students in Ho Chi Minh City.

Trust in AI, as Ofosu-Ampong et al. (2023) put it, means how much users believe an AI system is reliable, accurate, transparent, and secure when it comes to helping them make decisions. When students really understand what AI is all about, what it can do, where it falls short, and how it actually works, they start trusting these systems more (Abdelkader, 2023). That's especially important in universities, where everything hinges on accuracy, objectivity, and the safe handling of information (Al-Momani, 2023). Baek and Kim (2023) say it outright: trust comes first if you want people to accept and use AI tools like ChatGPT in their daily studies. Theoretical models back this up. Both the extended Technology Acceptance Model and Rogers' Diffusion of Innovations Theory explain that first impressions of any new technology lay the groundwork for psychological reactions such as trust, and that trust ultimately shapes whether people actually use the technology (Ali, Yasar, Ali, & Dogan, 2023; Lim, Gunasekara, Pallant, Pallant, & Pechenkina, 2023). Research shows there's a tight link between knowing about AI and trusting it. Niu and Mvondo (2024) found that people who understand AI better tend to set more realistic expectations for its performance, which leads to stronger trust. When students trust an AI, they see it as more helpful, their worries drop, and they are more likely to try it in their studies. Communicating clearly about how AI systems work, how they handle data, and what security measures are in place helps maintain transparency, which further builds trust (Abdelkader, 2023; Ofosu-Ampong et al., 2023; Shahzad et al., 2024). In short, trust is right at the heart of why students decide to use tools like ChatGPT for learning. Tactics like digital literacy programs, greater transparency about how AI works, and a focus on AI education all strengthen that trust. In the end, this is how the use and impact of AI-powered learning tools in Vietnamese colleges and universities can be enhanced. Based on the above arguments, the following mediating hypothesis is proposed.

H_{3-6}: Trust (TRU) mediates the relationship between AI Awareness (AIA) and Behavioral Intention (BI) to use ChatGPT for learning among university students in Ho Chi Minh City.

Based on the proposed hypotheses, the research model is presented below in Figure 4.

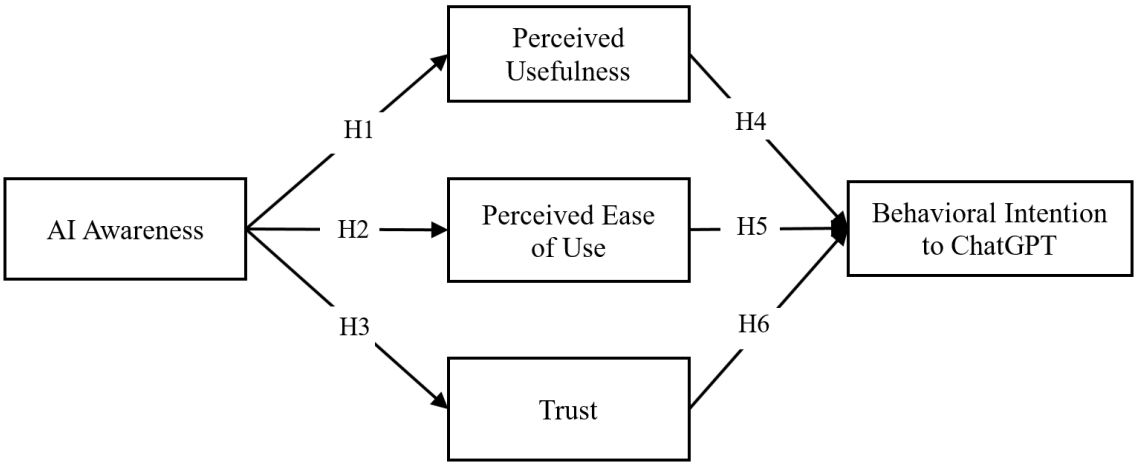


Figure 4. Proposed research model.

3. METHOD

3.1. Research Design and Data Collection

Survey Administration Period: The authors used a mixed-methods approach, integrating quantitative and qualitative research. They conducted a formal survey from April through May 5, 2026. Before participation, all respondents were informed about the study objectives, confidentiality measures, voluntary participation, and

© 2026 Conscientia Beam. All Rights Reserved.

withdrawal rights. Informed consent was obtained from all subjects involved in the study. Written informed consent was obtained from the seven participants involved in the focus-group discussions. For the pilot study (n = 128) and the main survey (n = 300 valid responses), participants provided electronic informed consent before completing the online questionnaire.

Qualitative research: The authors used R and the Biblioshiny 5.0 package to conduct a bibliometric analysis. They examined 1,362 papers from the Scopus database published between 2023 and 2026, working alongside BIBLO AI 5.0. Their goal was to map intellectual trends, identify research patterns, and examine how publications and keywords related to ChatGPT and higher education are connected. They also reviewed several earlier studies related to their topic, including work by Le, Do, Tran, Dang, and Nguyen (2026); Parveen et al. (2024); Shahzad et al. (2024); Tarhini, Masa'deh, Al-Busaidi, Mohammed, and Maqableh (2017) and Truc, Ha, and Long (2024). The study also drew on established theoretical frameworks: the Theory of Planned Behavior (TPB) from Ajzen (1985); Ajzen (1991); Ajzen (2002) and Davis (1989), as well as the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003). To ensure that their tools were sound, the authors consulted experts in artificial intelligence and the academic uses of ChatGPT. They also held a focus group with seven participants to obtain feedback on the survey's measurement scales. After receiving input on wording, clarity, and relevance, they revised the questionnaire, retaining 24 observable variables and several demographic questions. Before administering the main survey, they conducted a pilot study with 128 participants to ensure that the measurement scales were reliable.

Quantitative research: Once the academic supervisor signed off on the research instrument, the actual survey began. Since this study used both qualitative and quantitative methods, I distributed 350 questionnaires and received all of them back. However, not every response met the criteria; after a careful review, I excluded 50 because they contained missing answers or inconsistent patterns. This left me with 300 valid questionnaires, representing an 85.7% response rate, which was satisfactory for a robust PLS-SEM analysis. I conducted all statistical analyses, including descriptive statistics and structural equation modeling, in R version 4.4.3. This ensured that everything remained flexible, reproducible, and easy to track. Each analytical step focused on testing the study's hypotheses and exploring potential mediating effects in the model.

3.2. Sampling Method

Hair, Black, Babin, and Anderson (2019) recommend at least 50 observations for exploratory factor analysis (EFA), with 100 or more preferred, while maintaining a minimum ratio of five observations per item. Given this research model's 24 observed variables, the minimum sample size is 120 people. Hair, Hult, Ringle, and Sarstedt (2022) set a higher bar, arguing that at least 155 observations are needed to detect even small path coefficients (0.11–0.20) in PLS-SEM at the 5% level. Comrey and Lee (1992) go further, suggesting that sample sizes of 300 to 500 are considered good to very good for structural equation modeling.

Vu, Bui, Nguyen, Nguyen, and Vu (2025) take the most cautious approach: when combining EFA and regression analysis, they recommend selecting the highest recommended sample size to ensure robust statistical results. Taking all that into account, the authors aimed high. They gathered responses from 350 people to meet or exceed these recommendations and ensure that the sample was both reliable and sufficiently large for their research model. They also checked for non-response bias. Using wave analysis, they compared early and late respondents. Independent-samples t-tests showed no meaningful differences ($p > 0.05$) between the two groups on the main constructs (AIA, PU, PEOU, TRU, and BI). That is a good sign; non-response bias is not an issue here. They did use convenience sampling because reaching a truly diverse student group during the semester would have been difficult. They tried to cover their bases by sending the survey across different disciplines and years, hoping to minimize bias as much as possible.

© 2026 Conscientia Beam. All Rights Reserved.

3.3. Measurement Scales

The measurement scales used in this investigation were adapted from earlier research by Shahzad et al. (2024), Strzelecki (2024), and Tarhini et al. (2017). With Cronbach's alpha coefficients exceeding the suggested cutoff of 0.70, these scales have proven highly reliable. Appendix A presents the detailed measurement scales and observable variables used to assess the constructs in this study, including their respective sources.

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Descriptive Statistics

Table 1 presents the descriptive statistics of the survey respondents, detailing their demographic characteristics, such as gender, major, academic year, and experience using ChatGPT. The numbers show that the group was evenly split by gender: 142 men (47.33%) and 158 women (52.67%). Most students came from Health Sciences (26.33%), followed by Economics (21%), Education (19.67%), Engineering (18%), and other fields (15%). Regarding academic year, third-year students made up the largest group (22%), followed by fourth-year students (21.67%), first-year students (21.33%), second-year students (19.67%), and finally fifth-year students (15.33%). Thus, the sample included students from every stage of their studies, maintaining a balanced composition. In terms of ChatGPT experience, students with low experience formed the largest group (34.33%), but not by much; those with moderate experience (33.67%) and high experience (32%) were not far behind. Overall, the sample included both new and experienced ChatGPT users. This mix provided a good snapshot of different perspectives and habits regarding the use of ChatGPT for learning.

Table 1. Demographic statistics.

Demographic characteristics	Category	Frequency	Percent
Gender	Male	142	47.33
	Female	158	52.67
Major	Economics	63	21
	Engineering	54	18
	Education	59	19.67
	Health Sciences	79	26.33
	Others	45	15
Academic Year	First-year	64	21.33
	Second-year	59	19.67
	Third-year	66	22
	Fourth-year	65	21.67
	Fifth-year	46	15.33
Experience Using ChatGPT	Low	103	34.33
	Medium	101	33.67
	High	96	32

4.1.2. Measurement Model Assessment

Table 2 presents the results of the measurement model assessment, summarizing the reliability, convergent validity, and discriminant validity of the constructs. The measurement model checks out across the board. Every construct reached solid levels of convergent validity and reliability. The Composite Reliability (CR) scores fell between 0.825 and 0.896, well above the standard cutoff of 0.70. Cronbach's alpha values landed between 0.718 and 0.854, so internal consistency looks good, too. Average Variance Extracted (AVE) came in between 0.542 and 0.633, all clearing the required 0.50 mark (Hair et al., 2022). When it comes to discriminant validity, the HTMT values ranged from 0.526 to 0.823, comfortably below (Henseler, Ringle, & Sarstedt, 2015) threshold of 0.85. That means the constructs are distinct enough from each other. In short, the measurement model passed the tests for discriminant validity, convergent validity, and reliability. That gives a solid foundation for moving ahead with the structural model analysis.

© 2026 Conscientia Beam. All Rights Reserved.

Table 2. Results of the measurement model assessment.

Construct	Alpha	CR (rho_c)	AVE	HTMT Discriminant Validity			
				AIA	PEOU	PU	TRU
AIA	0.836	0.884	0.604				
PEOU	0.805	0.865	0.561	0.607			
PU	0.791	0.856	0.544	0.650	0.526		
TRU	0.718	0.825	0.542	0.751	0.623	0.604	
BI	0.854	0.896	0.633	0.821	0.670	0.550	0.823

4.1.3. Structural Model Results

Before testing the relationships we had hypothesized, we checked how well the overall model fit the data. We used several recommended indicators for PLS-SEM (Hair et al., 2022). You can see the details in Table 3. The SRMR was 0.076 for the saturated model and 0.095 for the estimated model. For discrepancy, d_ULS was 1.730, and d_G was 1.177. The NFI was 0.665. Altogether, these results show that our proposed model fits the data well enough to proceed with evaluating the structural relationships.

Table 3. Model fit indices.

Model fit index	Saturated model	Estimated model
SRMR	0.076	0.095
d_ULS	1.730	2.699
d_G	1.177	1.289
NFI	0.665	0.654

A non-parametric bootstrapping method was used to assess the significance of the structural associations (Hair et al., 2022). Because the associated t-values were greater than the critical value of 1.96, and the 95% bootstrap confidence intervals excluded zero, all direct hypotheses were supported, as shown in Table 4.

In particular, Perceived Usefulness (PU) ($\beta = 0.541$, $t = 6.124$), Perceived Ease of Use (PEOU) ($\beta = 0.505$, $t = 5.666$), and Trust (TRU) ($\beta = 0.596$, $t = 7.424$) were all significantly influenced by AI Awareness (AIA). Trust had a positive influence on behavioural intention (BI) ($\beta = 0.453$, $t = 8.056$), followed by Perceived Usefulness ($\beta = 0.128$, $t = 2.194$) and Perceived Ease of Use ($\beta = 0.293$, $t = 6.118$). These results show that the key factor influencing students' inclination to use ChatGPT for educational purposes is their level of trust in the platform. Regarding these relationships, the standardised indirect effects were computed by multiplying the standardised path coefficients from the mediator to the dependent variable and from the independent variable to the mediator (Hair et al., 2022). The findings showed that AI Awareness (AIA) had an effect on Behavioural Intention (BI) through Trust (TRU) = 0.270 (= 0.596 × 0.453), Perceived Ease of Use (PEOU) = 0.148 (= 0.505 × 0.293), and Perceived Usefulness (PU) = 0.069 (= 0.541 × 0.128). With a 95% bootstrapped confidence interval of [0.289, 0.641], the total indirect effect of AIA on BI reached $\beta = 0.487$ ($t = 5.295$), demonstrating the mediating roles of PU, PEOU, and TRU in the association between AI Awareness and ChatGPT usage behaviour for learning. Among the three mediators, Trust (TRU) showed the strongest mediating effect, indicating that students who are more informed about AI are more likely to develop trust in AI technologies, thereby significantly increasing their intention to use ChatGPT for academic purposes.

The coefficient of determination (R^2) was used to assess the structural model's explanatory capacity (Hair et al., 2022). Table 5 illustrates that AI Awareness accounted for 25.5% of the variance in perceived ease of use, 29.2% of the variance in perceived usefulness, and 35.5% of the variance in trust. Together, Perceived Usefulness, Perceived Ease of Use, and Trust accounted for 52.0% of the variation in Behavioral Intention, demonstrating a moderate degree of explanatory power. AI awareness had significant effects on trust ($f^2 = 0.551$), perceived usefulness ($f^2 = 0.413$), and perceived ease of use ($f^2 = 0.343$), according to the effect size (f^2) analysis. Trust had the greatest influence ($f^2 = 0.296$) among the predictors of behavioral intention, followed by perceived ease of use ($f^2 = 0.122$) and perceived usefulness ($f^2 = 0.027$) (Hair et al., 2022).

© 2026 Conscientia Beam. All Rights Reserved.

Table 4. Path results.

Hypothesis	Relationship	Standardized Path Coefficient (β)	Sample Mean	Standard Deviation	t-value	95% Bootstrap Confidence Interval	VIF	Decision
Direct Effect								
H1	AIA → PU	0.541	0.536	0.088	6.124	[0.336; 0.688]	N/A	Supported
H2	AIA → PEOU	0.505	0.504	0.089	5.666	[0.308; 0.655]	N/A	Supported
H3	AIA → TRU	0.596	0.595	0.080	7.424	[0.404; 0.723]	N/A	Supported
H4	PU → BI	0.128	0.128	0.058	2.194	[0.022; 0.243]	1.370	Supported
H5	PEOU → BI	0.293	0.291	0.048	6.118	[0.200; 0.385]	1.394	Supported
H6	TRU → BI	0.453	0.449	0.056	8.056	[0.336; 0.560]	1.443	Supported
Indirect Effect								
H1-4	AIA → PU → BI	0.069	0.069	0.092	5.295	[0.289; 0.641]		Supported
H2-5	AIA → PEOU → BI	0.148	0.148					
H3-6	AIA → TRU → BI	0.270	0.270					

Table 5. Results of R^2 and effect size (f^2).

Variable	R-square	R-square adjusted
PEOU	0.255	0.253
PU	0.292	0.290
TRU	0.355	0.353
BI	0.520	0.515
Relationship	f^2	Interpretation
AIA → PEOU	0.343	Large
AIA → PU	0.413	Large
AIA → TRU	0.551	Large
PEOU → BI	0.122	Small-to-medium
PU → BI	0.027	Small
TRU → BI	0.296	Medium

Figure 5 illustrates the final structural model, displaying the standardized path coefficients and the variance explained (R^2) for each endogenous construct in the research framework. Blindfolding was used to assess the model's predictive relevance. The model was tested for Perceived Ease of Use, yielding a value of 0.133. For Perceived Usefulness, the value was 0.142. The result for Trust was 0.177, and for Behavioral Intention, it was 0.311. These results are satisfactory because they are all greater than zero, indicating that the model has predictive relevance for all the constructs evaluated.

We also used the PLSpredict approach to assess how well the model could predict outcomes it had not seen before. The results were positive. We compared our model with a linear model, and our model was better at predicting outcomes in 14 of the 19 tests. The results for the other tests were remarkably close. This means that our model is effective at predicting outcomes, as the developers of the PLSpredict approach indicated it should. They stated that a model with results like these can predict outcomes. Appendix B presents the comprehensive results of the PLSpredict analysis, including the RMSE values for both the PLS-SEM and linear model (LM), along with the Q^2 predict values for each indicator.

© 2026 Conscientia Beam. All Rights Reserved.

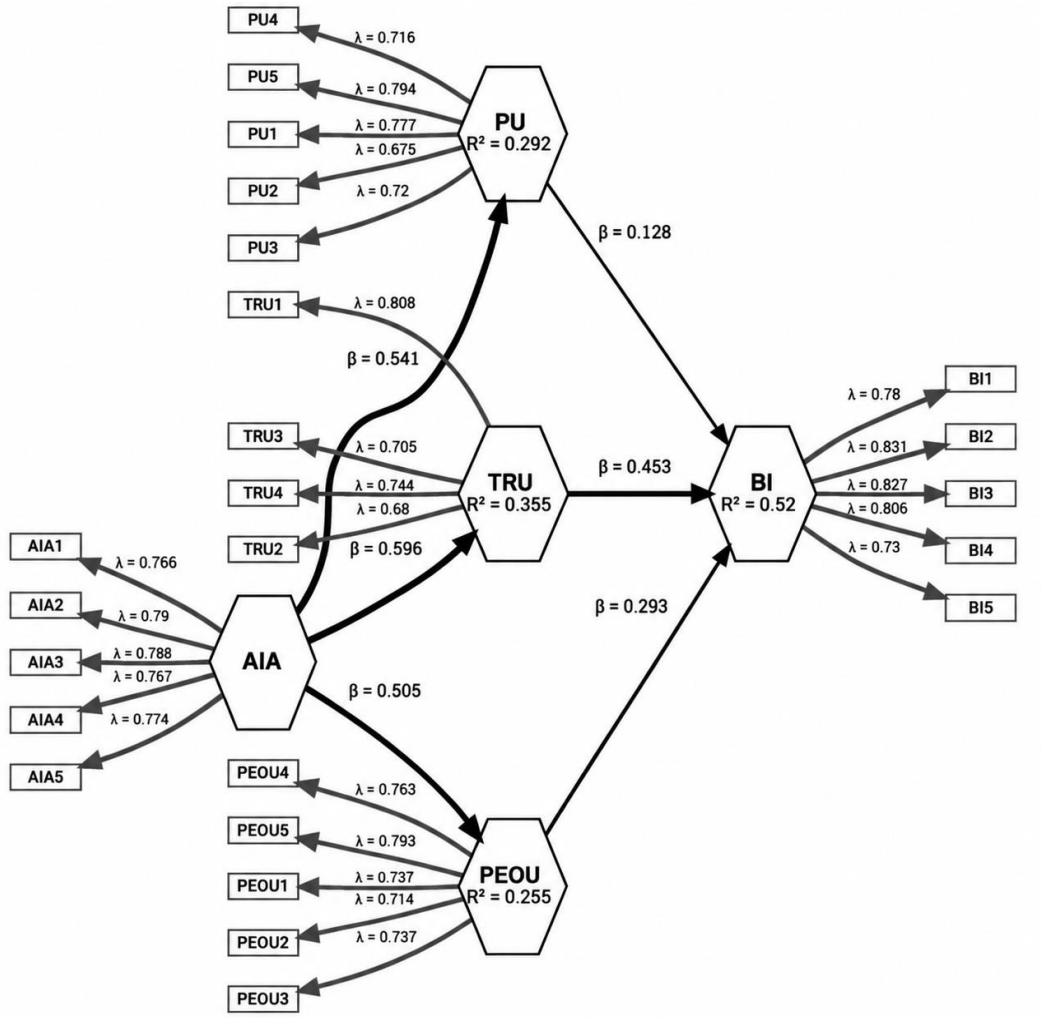


Figure 5. Structural Model.

This study used (Kock, 2015) comprehensive collinearity evaluation, an alternative to Harman's single-factor test, to investigate the possible impact of common method bias (CMB). All the Variance Inflation Factor (VIF) values, as shown in Table 6, fell considerably below the conservative cutoff of 3.3, ranging from 2.034 to 2.485. These findings suggest that multicollinearity and common method bias are not significant issues in the current investigation.

Table 6. Predictive relevance, full collinearity assessment and predictive performance.

Construct	Q^2	Full VIF
AIA	**N/A**	2.234
PEOU	0.133	2.321
PU	0.142	2.485
TRU	0.177	2.193
BI	0.311	2.034
Number of Indicators	PLS RMSE < LM RMSE	Interpretation
19	14	Moderate predictive power

Armstrong and Overton (1977)'s early–late respondent comparison method was used to investigate possible non-response bias. Welch's independent-samples t-tests revealed no significant differences between early and late responders across all research constructs ($p > 0.05$), as Table 7 illustrates. Additionally, there were very few mean differences between the two groups. These data imply that non-response bias is not a major issue and is unlikely to jeopardize the validity or generalizability of the findings.

© 2026 Conscientia Beam. All Rights Reserved.

Table 7. Non-response bias assessment.

Construct	Early mean	Late mean	p-value	Conclusion
AIA	4.50	4.53	0.729	No significant difference
PEOU	4.18	4.01	0.072	No significant difference
PU	4.36	4.41	0.554	No significant difference
TRU	4.55	4.48	0.332	No significant difference
BI	4.59	4.58	0.954	No significant difference

4.2. Discussion

First, the results show that AI Awareness (AIA) significantly and favorably affects the three cognitive antecedents: Trust (TRU) ($\beta = 0.596$), Perceived Usefulness (PU) ($\beta = 0.541$), and Perceived Ease of Use (PEOU) ($\beta = 0.505$). AI Awareness had the most influence on Trust among these relationships, suggesting that students' comprehension of AI's potential, advantages, and constraints is a necessary precondition for gaining confidence in ChatGPT. These results are in line with those of Shahzad et al. (2024), who similarly found that AI awareness has a beneficial impact on PEOU ($\beta = 0.258$) and PU ($\beta = 0.431$). Nonetheless, the path coefficients found in this study are significantly larger, indicating that AI Awareness has a greater influence on Vietnamese university students' favorable opinions of ChatGPT. This discrepancy could be explained by the rapid spread of generative AI technology in Vietnam, as well as widespread media attention and the growing use of AI tools in higher education. As a result, Vietnamese students' opinions of ChatGPT's utility, usability, and reliability are improving as they become more conscious of its practical significance.

Second, Behavioral Intention (BI) was found to be positively impacted by Perceived Usefulness (PU) ($\beta = 0.128$). This effect is significantly smaller than the similar effect of Performance Expectancy (PE) ($\beta = 0.260$) found by Strzelecki (2024) in Poland, but it is larger than that reported by Shahzad et al. (2024) ($\beta = 0.082$) in the Chinese setting. Although PU has a statistically significant impact on Behavioral Intention, its relatively small effect size indicates that Vietnamese students acknowledge ChatGPT as a helpful teaching technology; nonetheless, adoption is not primarily driven by usefulness. According to this research, students typically view ChatGPT as an additional educational tool that enhances, rather than significantly improves, their academic performance.

Third, with a path coefficient of $\beta = 0.293$, Perceived Ease of Use (PEOU) has a considerable impact on Behavioral Intention (BI). The current study shows a far stronger influence than the results reported by Strzelecki (2024), in which the similar construct, Effort Expectancy (EE), showed a path coefficient of just $\beta = 0.079$. However, compared with the $\beta = 0.694$ published by Shahzad et al. (2024), this coefficient is still much lower. These results show that ChatGPT's ease of use, accessibility, and user-friendly interface are significant factors motivating Vietnamese students to use AI in the classroom. However, the impact of usability is not as strong as in the Chinese setting, which may be attributed to variations in learning environments, the extent to which AI is incorporated into instructional strategies, and students' prior experiences with ChatGPT.

Fourth, with a path coefficient of $\beta = 0.453$, Trust (TRU) was found to be the most significant driver of Behavioral Intention. This result emphasizes that the primary driving force behind ChatGPT's acceptance for educational purposes is students' trust in its correctness, dependability, and security. The current study further shows that trust serves as the strongest direct predictor of students' behavioral intention, consistent with Shahzad et al. (2024), who viewed trust as a key factor underlying ChatGPT acceptance. This result builds on earlier research by highlighting that, in the context of Vietnamese higher education, building trust in AI technologies is crucial for fostering favorable perceptions and directly influencing students' willingness to incorporate ChatGPT into structured learning activities.

Lastly, the suggested model has a modest degree of explanatory power, explaining 52.0% of the variance in behavioral intention ($R^2 = 0.520$). This figure indicates satisfactory explanatory capability for behavioral research in educational contexts, although it is lower than the values reported by Strzelecki (2024) ($R^2 = 0.728$) and Shahzad et al. (2024) ($R^2 = 0.710$). The simplistic nature of the suggested model, which focuses primarily on the psychological

© 2026 Conscientia Beam. All Rights Reserved.

mechanisms of AI Awareness, Perceived Usefulness, Perceived Ease of Use, and Trust, may account for the lower R^2. Previous research, on the other hand, used extended UTAUT2 frameworks that included additional exogenous variables, such as habit and hedonic motivation, which often provide greater explanatory power for technology adoption behavior. However, the current results demonstrate that, in the context of Vietnamese higher education, combining AI Awareness, Trust, and the fundamental concepts of the Technology Acceptance Model (TAM) creates a solid and theoretically significant framework for understanding university students' intentions to use ChatGPT.

5. CONCLUSION AND IMPLICATIONS

5.1. Conclusion

Higher education now faces both new potential and challenges due to the rapid development of generative artificial intelligence. This study integrated three theoretical perspectives, the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Planned Behavior (TPB), and the Technology Acceptance Model (TAM), to investigate how AI Awareness influences university students' behavioral intention to use ChatGPT for learning. This study proposed and validated a multiple-mediation framework in which Perceived Usefulness, Perceived Ease of Use, and Trust jointly explain how AI Awareness is translated into students' intention to adopt ChatGPT, in contrast to many prior studies that focused on the direct determinants of technology adoption.

The empirical results verify that ChatGPT acceptance is fundamentally preceded by AI awareness. AI awareness increases students' perceptions of utility and ease of use while also bolstering their trust in AI systems, rather than merely influencing behavioral intention through direct cognitive appraisal. Trust emerged as the most significant pathway among these mediating mechanisms, suggesting that students' faith in the dependability, transparency, and legitimacy of AI technology is crucial for promoting educational adoption. These results imply that raising AI literacy alone is insufficient unless it is coupled with initiatives to build users' confidence in and favorable opinions of AI-assisted learning.

This paper makes three significant theoretical contributions to the expanding body of research on AI acceptance in higher education. First, by treating AI awareness as an upstream antecedent rather than an external variable, it extends conventional technology acceptance research. Second, it enhances TAM, TPB, and UTAUT by showing that technology adoption is motivated by a variety of interrelated psychological factors rather than discrete, direct effects. Third, this study offers a comprehensive research methodology that not only identifies emerging research trends but also empirically confirms the underlying behavioral mechanisms influencing ChatGPT adoption by integrating bibliometric analysis with PLS-SEM.

Additionally, a significant contextual gap identified through the bibliometric analysis is addressed in this work. Although prior studies have mostly focused on Western nations, factual data from emerging economies remain scarce. This study expands the applicability of current technology adoption theories to a developing-country setting and provides evidence from a rapidly digitalizing higher education environment by examining university students in Vietnam. Consequently, the research advances our understanding of how AI awareness affects the adoption of educational technology across diverse cultural and educational contexts.

Overall, by providing a more thorough explanation of ChatGPT acceptance in higher education, this study accomplishes its research goals. The results show that developing trust and fostering positive perceptions of technology, which in turn influence students' behavioral intentions to use AI-powered learning tools, are just as important to the successful application of generative AI in education as students' awareness of AI technologies.

5.2. Managerial Implications

"First, increasing students' awareness of ChatGPT and artificial intelligence. The results indicate that AI awareness (AIA) has a positive effect on ChatGPT Behavioral Intention (BI) in learning and positive effects on Perceived Usefulness (PU) ($\beta = 0.541$), Perceived Ease of Use (PEOU) ($\beta = 0.505$), and Trust in AI (TRU) ($\beta =$

© 2026 Conscientia Beam. All Rights Reserved.

0.596). Colleges should expand their communication campaigns, workshops, seminars, and training programs to help students better understand the potential, benefits, and limitations of AI technology. Institutions should also teach students how to use ChatGPT effectively for academic purposes, craft appropriate prompts, and critically evaluate AI-generated content, in addition to providing basic AI knowledge. The more students knew about AI, the more likely they were to consider ChatGPT useful, easy to use, and reliable.

Second, enhance students' trust in AI technologies, including ChatGPT in this case. Results indicate that Trust in AI (TRU) has the highest direct impact on ChatGPT Behavioral Intention (BI) ($\beta = 0.453$). Moreover, the indirect effect of AIA on BI via TRU ($\beta = 0.270$) is stronger than those of the other two mediating mechanisms. This implies that trust is a crucial factor in prompting students to adopt and use ChatGPT. Therefore, educational institutions need to foster a transparent AI environment by teaching students to verify information, recognize the limitations of AI systems, and utilize ChatGPT as a tool, not a substitute for critical thinking. Raising student awareness of the accuracy, consistency, and reliability of AI-generated output can help build trust and promote more effective use of ChatGPT.

Third, increasing the perceived ease of use of ChatGPT for learning. The results indicate that Perceived Ease of Use (PEOU) has a positive effect on the Behavioral Intention of AI (BI) ($\beta = 0.293$) and is a mediator between AIA and BI ($\beta = 0.148$). This suggests that if students find ChatGPT easy and accessible to use, they will be more likely to use it frequently. Therefore, universities should arrange practical training sessions, develop user guides tailored to different disciplines, and provide practical examples of how to incorporate the chatbot into learning and research activities. Lowering technical barriers can make it easier for students to adopt and use AI tools effectively.

Fourth, to stress the usefulness of ChatGPT in the learning process. The results indicate that Perceived Usefulness (PU) positively impacts the Behavioral Intention (BI) of ChatGPT ($\beta = 0.128$), and it mediates the relationship between AIA and BI ($\beta = 0.069$). Its effect is smaller than those of trust and ease of use, but PU remains an important factor in encouraging students to use the chatbot. Hence, universities and instructors should facilitate students' use of ChatGPT for tasks such as literature searches, content summarisation, report writing, explaining academic concepts, and generating research ideas. Students are more inclined to use ChatGPT in their learning when they recognise its practical advantages.

In short, the results suggest that promoting ChatGPT Behavioral Intention (BI) in learning depends not only on students' AI awareness (AIA) but also on the mediating roles of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and, most importantly, Trust in AI (TRU). TRU was the strongest mediator among these factors. Therefore, universities should adopt holistic strategies that simultaneously improve awareness, trust, and the user experience of AI to optimise the impact of AI adoption in higher education.

5.3. Limitations and Future Research Directions

5.3.1. Limitations

Although the study has achieved its objectives, there are some limitations that need to be mentioned.

First, since the use of ChatGPT and AI in general is still relatively new in Vietnam, the current domestic literature on the subject is limited. Therefore, this study used foreign literature as its main source.

Second, the study utilized a convenience sample of 300 university students in Ho Chi Minh City, which might not accurately represent the target population.

Third, due to resource availability, the survey was conducted only in Ho Chi Minh City, which might affect the accuracy of generalizing the results to other regions in Vietnam.

Fourth, the study included only four factors: AI awareness (AIA), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Trust in AI (TRU). Although the model showed that these factors explained 51.5% of the variance in ChatGPT Behavioral Intention (Adjusted $R^2 = 0.515$), other factors affecting behavioral intention may not have been considered.

© 2026 Conscientia Beam. All Rights Reserved.

5.3.2. Future Research Directions

To enhance the representativeness and generalizability of the results, future research should first consider expanding the poll's scope to include additional provinces and cities.

Second, to ensure the reliability and validity of future research findings, probability sampling methods and larger sample sizes should be used.

Third, to explore differences in ChatGPT behavioral intention across user categories, future research should consider including instructors, postgraduate students, and working professionals as target populations.

Fourth, to improve the model's ability to explain ChatGPT behavioral intention in an educational context, future research should consider incorporating additional variables, such as attitudes toward AI, social impact, digital literacy, perceived risk, and facilitating conditions.

Funding: This study received no specific financial support.
Institutional Review Board Statement: This study was conducted in line with the ethical standards of the Declaration of Helsinki and its subsequent amendments. Ethical approval for all research procedures involving human participants was granted by the Ethical Committee of the Faculty of Business Administration at Industrial University of Ho Chi Minh City, Vietnam, on (27 December 2025) under (Reference No. 27122025). The ethical review confirmed that the study posed minimal risk to participants and complied with institutional guidelines for social science research.
Informed Consent Statement: Written informed consent was obtained from the focus-group participants, while electronic informed consent was obtained from participants in both the pilot study and the main online questionnaire. Participation was voluntary, and participants were informed of their right to withdraw from the study at any time without penalty. All data were anonymized to protect participant confidentiality.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Disclosure of AI Use: The authors used OpenAI's ChatGPT and Google's NotebookLM to edit and refine the wording of the manuscript. All outputs were reviewed and verified by the authors.

REFERENCES

Abdelkader, O. A. (2023). ChatGPT's influence on customer experience in digital marketing: Investigating the moderating roles. *Heliyon, 9*(8), e18770. https://doi.org/10.1016/j.heliyon.2023.e18770

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action control: From cognition to behavior* (pp. 11-39). Berlin, Germany: Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665-683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Al-Abdullatif, A. M. (2023). Modeling students' perceptions of chatbots in learning: Integrating technology acceptance with the value-based adoption model. *Education Sciences, 13*(11), 1151. https://doi.org/10.3390/educsci13111151

Al-Emran, M., Arpaci, I., & Salloum, S. A. (2020). An empirical examination of continuous intention to use m-learning: An integrated model. *Education and Information Technologies, 25*(4), 2899-2918. https://doi.org/10.1007/s10639-019-10094-2

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology Acceptance Model in M-learning context: A systematic review. *Computers & Education, 125*, 389-412. https://doi.org/10.1016/j.compedu.2018.06.008

Al-Momani, A. M. (2023). Adoption of artificial intelligence and robotics in healthcare: A systematic literature review. *International Journal of Contemporary Management and Information Technology, 3*(6), 1-16.

Ali, D., Fatemi, Y., Boskabadi, E., Nikfar, M., Ugwuoke, J., & Ali, H. (2024). ChatGPT in teaching and learning: A systematic review. *Education Sciences, 14*(6), 643. https://doi.org/10.3390/educsci14060643

© 2026 Conscientia Beam. All Rights Reserved.

Ali, F., Yasar, B., Ali, L., & Dogan, S. (2023). Antecedents and consequences of travelers' trust towards personalized travel recommendations offered by ChatGPT. *International Journal of Hospitality Management*, *114*, 103588. https://doi.org/10.1016/j.ijhm.2023.103588

Almogren, A. S., Al-Rahmi, W. M., & Dahri, N. A. (2024). Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective. *Heliyon*, *10*(11), e31887. https://doi.org/10.1016/j.heliyon.2024.e31887

Alshurideh, M., Al Kurdi, B., Salloum, S. A., Arpaci, I., & Al-Emran, M. (2023). Predicting the actual use of m-learning systems: A comparative approach using PLS-SEM and machine learning algorithms. *Interactive Learning Environments*, *31*(3), 1214-1228. https://doi.org/10.1080/10494820.2020.1826982

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396-402. https://doi.org/10.1177/002224377701400320

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

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, *7*(1), 52-62. https://doi.org/10.61969/jai.1337500

Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies*, *29*(5), 6357-6382. https://doi.org/10.1007/s10639-023-12076-x

Caratiquit, K. D., & Caratiquit, L. J. C. (2023). ChatGPT as an academic support tool on the academic performance among students: The mediating role of learning motivation. *Journal of Social, Humanity, and Education*, *4*(1), 21-33. https://doi.org/10.35912/jshe.v4i1.1558

Comrey, A. L., & Lee, H. B. (1992). *A first course in factor analysis* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

de Andrés-Sánchez, J., & Gené-Albesa, J. (2023). Explaining policyholders' chatbot acceptance with an unified technology acceptance and use of technology-based model. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(3), 1217-1237. https://doi.org/10.3390/jtaer18030062

Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International*, *61*(3), 460-474. https://doi.org/10.1080/14703297.2023.2195846

Fütterer, T., Fischer, C., Alekseeva, A., Chen, X., Tate, T., Warschauer, M., & Gerjets, P. (2023). ChatGPT in education: Global reactions to AI innovations. *Scientific Reports*, *13*(1), 15310. https://doi.org/10.1038/s41598-023-42227-6

Gumbo, L. C., Halimani, D., & Diza, M. (2017). Perceived usefulness (PU) and perceived ease of use (PEOU) as key drivers of mobile banking adoption: A case of Zimbabwe. *Journal of Corporate Governance, Insurance, and Risk Management*, *4*(1), 87-105. https://doi.org/10.56578/jcgirm040106

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Andover, Hampshire, UK: Cengage Learning EMEA.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Los Angeles, CA: SAGE Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Jang, S.-J. (2024). A case study of ChatGPT on university students' self-regulated learning. In *Progress in education* (Vol. 82, pp. 27-49). New York, NY: Nova Science Publishers.

© 2026 Conscientia Beam. All Rights Reserved.

Jo, H. (2025). Decoding the ChatGPT mystery: A comprehensive exploration of factors driving AI language model adoption. *Information Development*, *41*(3), 875-895. https://doi.org/10.1177/02666669231202764

Khalid, N. (2014). *The role of perceived usefulness and perceived enjoyment in assessing students' intention to use LMS using 3-TUM.* Paper presented at the Proceedings of the Global Summit on Education (GSE 2014), Kuala Lumpur, Malaysia: WorldConferences.net.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1-10. https://doi.org/10.4018/ijec.2015100101

Lai, C. Y., Cheung, K. Y., & Chan, C. S. (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*, *5*, 100178. https://doi.org/10.1016/j.caeai.2023.100178

Le, T. M. D., Do, H. T. N., Tran, K. M., Dang, V. T., & Nguyen, B. K. H. (2026). Integrating TAM and UGT to explore students' motivation for using ChatGPT for learning in Vietnam. *Journal of Research in Innovative Teaching & Learning*, *19*(1), 178-193. https://doi.org/10.1108/JRIT-05-2024-0116

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & 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*, *21*(2), 100790. https://doi.org/10.1016/j.ijme.2023.100790

Limna, P., Kraiwanit, T., Jangjarat, K., Klayklung, P., & Chocksathaporn, P. (2023). The use of ChatGPT in the digital era: Perspectives on chatbot implementation. *Journal of Applied Learning & Teaching*, *6*(1), 64-74.

Lin, Y., & Yu, Z. (2023). Extending technology acceptance model to higher-education students' use of digital academic reading tools on computers. *International Journal of Educational Technology in Higher Education*, *20*(1), 34. https://doi.org/10.1186/s41239-023-00403-8

Lo, C. K., Hew, K. F., & Jong, M. S.-Y. (2024). The influence of ChatGPT on student engagement: A systematic review and future research agenda. *Computers & Education*, *219*, 105100. https://doi.org/10.1016/j.compedu.2024.105100

Maheshwari, G. (2024). Factors influencing students' intention to adopt and use ChatGPT in higher education: A study in the Vietnamese context. *Education and Information Technologies*, *29*(10), 12167-12195. https://doi.org/10.1007/s10639-023-12333-z

Memarian, B., & Doleck, T. (2023). ChatGPT in education: Methods, potentials, and limitations. *Computers in Human Behavior: Artificial Humans*, *1*(2), 100022. https://doi.org/10.1016/j.chbah.2023.100022

Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the Technology Acceptance Model (TAM) in combination with the Technology–Organisation–Environment (TOE) framework. *Buildings*, *12*(2), 90. https://doi.org/10.3390/buildings12020090

Niu, B., & Mvondo, G. F. N. (2024). I am ChatGPT, the ultimate AI chatbot! Investigating the determinants of users' loyalty and ethical usage concerns of ChatGPT. *Journal of Retailing and Consumer Services*, *76*, 103562. https://doi.org/10.1016/j.jretconser.2023.103562

Ofosu-Ampong, K., Acheampong, B., Kevor, M.-O., & Amankwah-Sarfo, F. (2023). Acceptance of artificial intelligence (ChatGPT) in education: Trust, innovativeness and psychological need of students. *Information and Knowledge Management*, *13*(4), 37–47. https://doi.org/10.7176/IKM/13-4-03

Parveen, K., Phuc, T. Q. B., Alghamdi, A. A., Hajjej, F., Obidallah, W. J., Alduraywish, Y. A., & Shafiq, M. (2024). Unraveling the dynamics of ChatGPT adoption and utilization through structural equation modeling. *Scientific Reports*, *14*(1), 23469. https://doi.org/10.1038/s41598-024-74406-4

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In D. W. Stacks & M. B. Salwen (Eds.), *An integrated approach to communication theory and research* (2nd ed., pp. 432–448). New York, NY: Routledge.

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning & Teaching*, *6*(1), 342-363.

© 2026 Conscientia Beam. All Rights Reserved.

Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2023). Platform-independent and curriculum-oriented intelligent assistant for higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 42. https://doi.org/10.1186/s41239-023-00412-7

Sewandono, R. E., Thoyib, A., Hadiwidjojo, D., & Rofiq, A. (2023). Performance expectancy of e-learning on higher institutions of education under uncertain conditions: Indonesia context. *Education and Information Technologies*, *28*(4), 4041-4068. https://doi.org/10.1007/s10639-022-11074-9

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*(1), 46. https://doi.org/10.1186/s41239-024-00478-x

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*(2), 223-245. https://doi.org/10.1007/s10755-023-09686-1

Tanvir, K., Islam, M. S., Sezan, S. B. K., Sanad, Z. A., & Ataur, A.-J. I. (2023). Impact of ChatGPT on academic performance among Bangladeshi undergraduate students. *International Journal of Research in Science & Engineering*, *3*(5), 18–28. https://doi.org/10.55529/ijrise.35.18.28

Tarhini, A., Masa'deh, R., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modeling approach. *Journal of International Education in Business*, *10*(2), 164-182. https://doi.org/10.1108/JIEB-09-2016-0032

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, *10*(1), 15. https://doi.org/10.1186/s40561-023-00237-x

Truc, P. T. T., Ha, L. T., & Long, B. T. (2024). Factors affecting the application of ChatGPT in learning among economics and law students. *Journal of Economy and Forecast*(10), 45-48.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Vu, N. B., Bui, H. K., Nguyen, T. N. L., Nguyen, T. H. V., & Vu, T. C. (2025). *Research methods in business and management: For students majoring in logistics and supply chain management*. Hanoi, Vietnam: Transport Publishing House.

Appendix A. Scales.

No.	Code	Questions	Source
AI Awareness (AIA)			
1	AIA1	I am aware that ChatGPT has evolved through versions such as 3.5 and 4.	Shahzad et al. (2024)
2	AIA2	ChatGPT helps me achieve better learning outcomes.	
3	AIA3	I have read or come across information about issues and limitations encountered by ChatGPT.	
4	AIA4	I know how to use ChatGPT effectively to support my learning objectives.	
5	AIA5	I am aware of both the benefits and risks of using ChatGPT for learning and examinations.	
Perceived Usefulness (PU)			
1	PU1	ChatGPT helps me accomplish my learning tasks more effectively.	Shahzad et al. (2024)
2	PU2	Using ChatGPT improves the quality of my learning.	
3	PU3	ChatGPT effectively answers my academic questions and information needs.	
4	PU4	ChatGPT helps improve my learning performance and knowledge acquisition.	
5	PU5	I can easily find solutions to learning problems through ChatGPT anytime and anywhere.	
Perceived Ease of Use (PEOU)			
1	PEOU1	I find ChatGPT easy to use and easy to learn from the first time.	Shahzad et al. (2024)
2	PEOU2	I find ChatGPT easy to operate and understand.	

© 2026 Conscientia Beam. All Rights Reserved.

No.	Code	Questions	Source
3	PEOU3	I believe no complex skills are required to use ChatGPT.	
4	PEOU4	ChatGPT helps me search for learning information in a simple way.	
5	PEOU5	ChatGPT enables me to complete assignments and find answers easily.	
Trust (TRU)			
1	TRU1	I feel confident about the security of using ChatGPT for interactions.	Tarhini et al. (2017)
2	TRU2	I believe that using ChatGPT does not pose privacy risks.	
3	TRU3	I believe ChatGPT is capable of protecting users' privacy.	
4	TRU4	I trust ChatGPT to keep my personal data secure from unauthorized access.	
Behavioral Intention (BI)			
1	BI1	I am willing to use ChatGPT for learning and examinations if permitted.	Strzelecki (2024)
2	BI2	I will use ChatGPT whenever I need answers to academic questions.	
3	BI3	I am willing to use ChatGPT to support my learning and research.	
4	BI4	I believe using ChatGPT will enhance my learning effectiveness.	
5	BI5	I believe using ChatGPT is worthwhile because of the benefits it provides for learning.	

Appendix B. PLS predict results.

Indicator	RMSE (PLS)	RMSE (LM)	Q^2_predict
BI1	0.554	0.579	0.158
BI2	0.549	0.56	0.338
BI3	0.568	0.592	0.259
BI4	0.524	0.548	0.264
BI5	0.174	0.192	0.919
PEOU1	0.728	0.754	0.081
PEOU2	0.73	0.751	0.037
PEOU3	0.607	0.624	0.118
PEOU4	0.628	0.647	0.142
PEOU5	0.704	0.726	0.125
PU1	0.621	0.639	0.116
PU2	0.618	0.637	0.047
PU3	0.597	0.616	0.141
PU4	0.626	0.645	0.134
PU5	0.61	0.629	0.171
TRU1	0.583	0.601	0.245
TRU2	0.636	0.654	0.071
TRU3	0.524	0.541	0.327
TRU4	0.553	0.571	0.208

Views and opinions expressed in this article are the views and opinions of the author(s), Humanities and Social Sciences Letters shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content.

© 2026 Conscientia Beam. All Rights Reserved.