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A cross-national assessment of artificial intelligence (AI) Chatbot user perceptions in collegiate physics education

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A B S T R A C T

This study explores the perception of artificial intelligence (AI)-based Chatbots, specifically Open AI's ChatGPT use, among physics students in four universities in Ghana, Jordan, and the United States. We utilized a survey instrument adapted from the Technology Acceptance Model (TAM) to elicit responses from 804 students. TAM constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEU), Subjective Norms (SN), Attitude Towards Technology Use (ATU), Behavioral Intention (BI), and User Behavior (UB) were assessed. We also assessed perceptions of ethical use (EU) and student learning outcomes (SLO) using a Structural Equation Model (SEM) approach. A measurement model had good fit indices and validated most hypotheses. A path analysis (PA) for hypothesized relationships suggested PEU and SN are significant predictors of BI and UB, whereas PU's influence on BI was indirect. Significantly, EU concerns negatively moderated the relationship between BI and UB, suggesting that higher ethical concerns can reduce ChatGPT usage. Cross-cultural analysis uncovered significant differences in perceptions and usage patterns influenced by institutional policies, academic levels, and demographic factors. Our findings affirm TAM's robustness in predicting technology use across various cultural and institutional settings. Findings also underscore the crucial roles of social influence in fostering positive user behaviors for Chat GPT. This study provides insights for educators and policymakers to develop strategies for integrating AI Chatbots responsibly and effectively in collegiate physics education while addressing ethical concerns. A longitudinal survey of the relationships between consistent AI Chatbot use, institutional support, student motivation, and learning outcomes is recommended.

1. Introduction

1.1. *Artificial intelligence (AI) tools in higher education*

Artificial Intelligence (AI) tools have significantly transformed higher education by enhancing pedagogical practices (Crompton & Burke, 2023). AI tools have revolutionized the teaching and learning of subjects like collegiate-level physics (Zhai et al., 2021). The historical evolution of AI, attributed to foundational contributions by Alan Turing and John McCarthy, who coined the term "Artificial Intelligence," has led to the development of systems capable of performing tasks requiring human-like intelligence, such as learning, reasoning, perception, and decision-making (Collins et al., 2021; Crompton & Burke, 2023; McCorduck & Cfe, 2004). These advancements have been propelled by machine learning, deep learning, natural language processing, computer vision, and robotics, which are now integral to education (Górriz et al., 2020; Ilkka, 2018).

Extant studies have explored AI's impact across various academic disciplines. For example, Shukla et al. (2019) focused their research on AI in Engineering, Winkler-Schwartz et al. (2019) examined the use of AI in medical education, Liang et al. (2023) conducted a systematic review of AI's roles in language education, Hwang and Tu (2021) studied AI's use in mathematics education, and Hallal et al. (2023) studied the use of AI tools in chemistry education. These studies highlight AI technology as a prominent tool, offering innovative opportunities to enhance learning outcomes and educational efficiency in higher-level science education

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(Xu & Ouyang, 2022; Yannier et al., 2020).

AI tools that have utility, specifically in higher education, include a Chatbot, a computer program designed to simulate conversation with human users, especially over the Internet, answer questions, and provide personalized learning experiences (Okonkwo & Ade-Ibijola, 2021). These Chatbots serve as virtual assistants to students, offering real-time answers to queries (Clarizia et al., 2018; Crompton & Song, 2021). Chatbots simulate human communication, allowing users to interact with digital devices conversationally (Ciechanowski et al., 2019; Okonkwo & Ade-Ibijola, 2021).

1.2. Generative AI chatbots

Generative AI Chatbots are open-domain programs capable of generating original language combinations rather than relying on predefined responses (Adamopoulou & Moussiades, 2020; Codecademy, 2024). Open AI's ChatGPT, launched in 2022, has become one of the most widely discussed AI tools for educational purposes, capable of summarizing documents, critiquing, writing, and translating languages. Its functionalities make it a valuable asset for personalized learning experiences and real-time student assistance (Open AI ChatGPT, n.d.). ChatGPT is a large language model (LLM) capable of communicating with users in a human-like way and trained using reinforcement learning from human feedback, with a paid version having image and voice inputs (Open AI ChatGPT, n.d.).

Despite other generative AI Chatbots for educational purposes, we focused more on ChatGPT because of its popularity and perceived use among respondents in higher education, as suggested by Fütterer et al. (2023), who used topic modeling and sentiment analysis to examine global perceptions and reactions to ChatGPT in the context of higher education. The study revealed that ChatGPT triggered a massive response on Twitter, with education being the most tweeted content topic. Topics ranged from specific (e.g., cheating) to broad (e.g., opportunities), which were discussed with mixed sentiment. The findings offer valuable insights into public reactions to innovative technologies, with implications for research, policy communication, and practices in dynamic contexts. Stöhr et al. (2024) conducted a recent study on Chatbot use among Swedish university students, finding that a third regularly use ChatGPT for education, and about half of the students expressed positive attitudes toward using Chatbots in education, though almost as many expressed ethical concerns about future use.

Abdaljaleel et al. (2024) investigated the factors influencing university students' attitudes and usage of ChatGPT in five Arab countries. The researchers suggested that successfully integrating ChatGPT in higher education relies on the perceived ease of use, perceived usefulness, positive attitude towards technology, social influence, behavioral/cognitive elements, low anxiety, and minimal perceived risks. In a multinational study, Ibrahim et al. (2023) found that most students in Brazil, India, Japan, the UK, and the USA intend to use ChatGPT for assignment support. Many also anticipate peer endorsement of its use, suggesting a potential shift toward ChatGPT becoming standard practice among university students.

Maheshwari (2024) studied Vietnamese higher education students' intention to adopt and use ChatGPT using a variant of the Technology Acceptance Model (TAM) and found that students' inclination to adopt ChatGPT was influenced by their perception of "ease of use" (PEU). However, the perceived usefulness (PU) of ChatGPT did not directly impact students' intention to adopt it. Sallam et al. (2023) emphasized the importance of considering risk perceptions, usefulness, ease of use, attitudes, and behavioral factors when adopting ChatGPT in higher healthcare education. Habibi et al. (2023), in a study among higher education students in Indonesia, also found that ChatGPT use was most significantly predicted by behavioral intention (BI).

The selected countries for this study provided a practical setting to examine how diverse technological, educational, and socio-cultural contexts influence AI Chatbot use among collegiate physics students and to highlight challenges while recommending best practices. For a developing country like Ghana, extant studies suggest that AI use in educational settings has not received much attention, and knowledge of AI's terms, tasks, methodologies, and applications needs to be adopted to provide the groundwork for developing the sector (Gyamfi et al., 2022; Segbenya et al., 2023).

Segbenya et al. (2023) further suggest that constraints of broad-band data non-availability and internet connectivity, usually disrupted by electricity power outages and poor networks, pose challenges for AI use in higher educational settings in Ghana. The challenges are also exacerbated by the low awareness level of AI software among postgraduate students who must make informed decisions about what AI tools/software are for scholarly purposes.

Jordan's rapidly advancing science and technology focus in the educational sector has accelerated AI adoption in higher education, coupled with policies and regulations that have significantly impacted educational excellence (Al Najdawi, Shwedeh, Abdelmoghies, Kitana, & Ali, 2024; Alzyoud, 2023; Najwa et al., 2023). Finally, as a technologically resourced developed country, the US has a higher educational setting where AI adoption has been impactful (Crompton & Burke, 2023; U.S. Department of Education, 2023).

1.3. Gaps in ChatGPT and Technology Acceptance Model (TAM) research

The original Technology Acceptance Model (TAM) has five constructs: perceived ease of use (PEU), perceived usefulness (PU), attitude towards use (ATU), behavioral intention (BI), and User Behavior (UB) and postulates that perceptions of PU and PEU predict ATU of the technology and subsequent BI and UB (Davis, 1989; Ma & Liu, 2004; Venkatesh et al., 2003). Despite using TAM in higher education ChatGPT research (Al Darayseh, 2023; Maheshwari, 2024), specific studies assessing ChatGPT user behavior among collegiate physics students using the TAM seem minimal. This study sought to fill a theoretical gap by testing the utility of TAM among a cross-national and cultural population of collegiate physics students. Expanding research efforts to assess AI Chatbot use among collegiate physics students from technologically constrained and under-represented geographical regions such as Ghana also helps fill spatial gaps, as Ibrahim et al. (2023) and Maheshwari (2024) suggest.

Also, the ethical concerns about ChatGPT use make this study appropriate (Hutson et al., 2022; Popenici & Kerr, 2017). Evaluating the strength of these factors while considering the ethical concerns may inform policy formulation to ensure effective teaching, learning, and research. Segbenya et al. (2023) used the Socio-Technical Systems theory to assess the benefits and ethical challenges of AI Chatbot use among Ghanaian post-graduate graduate students. However, their population was drawn from only one university and did not include undergraduate students. They recommended a broader study to close a methodological gap by adding undergraduate students to future studies.

1.4. Research objectives

Using the TAM, we assessed the predictive factors of ChatGPT use among collegiate physics students at four universities in Ghana, Jordan, and the USA. Understanding respondents' use of ChatGPT can assist professors and teaching staff in developing syllabi and course outlines that leverage the strengths of these AI tools. Additionally, we explored the ethical use (EU) of ChatGPT, examining its impact on user behavior (UB) and students' self-reported learning outcomes (SLO). Recommendations for policies and practices were proffered based on our research findings.

1.5. Research questions

To achieve these objectives, we addressed the following research questions:

1. What are the strengths of relationships among TAM factors assessing respondents' perceptions of ChatGPT and user behavior?
2. How does the ethical use of ChatGPT influence the relationship between behavioral intentions and students' learning outcomes among respondents?
3. How does the ethical use of ChatGPT influence the relationship between behavioral intentions and user behavior of respondents?
4. How do behavioral intentions, user behavior, and student learning outcomes relate to the frequency of ChatGPT use in academic work?
5. What are the demographic differences in perceptions of TAM constructs (BI, UB) and student learning outcomes (SLO)?

2. Literature review

2.1. AI tools in collegiate-level science education

In collegiate science education, perceptions of AI technology and acceptance can significantly influence its applications and employment in designing curricula, teaching methods, and assessments to obtain effective learning (Eltabakh & Ahmed Ismail, 2019). Essel et al. (2022), in a pre-test and post-test study of a virtual teaching assistant's impact on science students in Ghanaian higher education, found that students who interacted with the chatbot outperformed those who interacted solely with the course instructor. The study also focused on the learning of the experimental cohort and their view regarding interaction with AI chatbots and suggested a potential benefit regarding productive student learning outcomes (SLO).

Al Darayseh (2023) used the TAM model to study teachers' perceptions of AI applications in science education in Abu Dhabi, United Arab Emirates, finding high acceptance of AI in classrooms. Positive correlations were observed with self-efficacy, ease of use, expected benefits, attitudes, and behavioral intentions. These studies suggest that using AI technology such as ChatGPT can enhance teaching effectiveness and potentially students' cognitive SLO and needs to be explored. Kubullek et al. (2024) investigated factors influencing students' attitudes toward AI technologies in university settings, comparing business and STEM programs. They recommended policies to guide educational technology implementation and strategies to integrate generative AI tools effectively, addressing diverse student needs in various academic contexts. McGrath et al. (2024) also suggested more studies in the nascent research area of AI chatbots in higher education, focusing on the future role of ChatGPT in higher education.

Rodway and Schepman (2023) examined projected course satisfaction using AI educational tools, and Schwenke et al. (2023), through an autoethnographic study, highlighted the benefits of ChatGPT in thesis writing, including brainstorming, structuring, and text revision. They also noted limitations, such as issues with referencing, emphasizing the need for continuous validation of ChatGPT-generated outcomes, which fosters deeper learning. Pursnani, Sermet, Kurt, and Demir (2023) examined the feasibility and effectiveness of using ChatGPT to achieve satisfactory performance on the Fundamentals of Engineering (FE) environmental examination. Hallal et al. (2023) assessed the performance and accuracy of two chatbots, ChatGPT and Bard, in understanding text-based structural notations answering organic chemistry-related questions. They concluded that while these AI chatbots show significant potential as educational tools in organic chemistry and may inspire new teaching strategies, their implementation requires careful monitoring due to rapid technological advancements.

2.2. Ethical concerns with AI tools in collegiate science education

Despite its potential benefits, integrating AI tools such as ChatGPT in collegiate science education raises ethical concerns about privacy, bias, and transparency (Gong et al., 2018; Hutson et al., 2022; Popenici & Kerr, 2017; Segbenya et al., 2023; Zhang & Aslan, 2021). Academic integrity risks, such as over-reliance on AI for assessments, have become an ongoing concern for faculty and college administrators. Baidoo-Anu and Owusu Ansah (2023) state that AI-generated-text detectors are ineffective with current sophisticated natural processing language models and that some students also have access to these detectors and can alter the text generated to ensure that they become undetectable. The ethical risks of perpetuating biases and discriminating against marginalized groups have been raised (Yadav & Heath, 2022). For instance, AI tools' algorithms can perpetuate gender and racial biases if the training data is biased (Bolukbasi et al., 2016), and the need for ethical frameworks to guide the implementation of AI scholarly tools in education has been suggested (Dwivedi et al., 2023).

AI tools that analyze and monitor students' performance data can pose privacy risks if mishandled or used without authorization (Veale & Binns, 2017). Data must be collected and used, respecting student privacy and autonomy (Nguyen et al., 2023; Parsons, 2021; Stein et al., 2024). AI tools can automate administrative tasks like grading and scheduling, allowing teachers to focus on teaching. However, they must not replace teachers, perpetuate biases, or contribute to discrimination (Holmes, 2023). Dwivedi et al. (2023) support this point and argue that with prolific use, AI tools can replace teachers, resulting in a loss of human connection, jobs, and personalized learning.

Though AI tools can provide personalized and adaptive learning experiences, support students' problem-solving skills, and reduce teachers' workload, they can also increase the risk of overreliance (Peres et al., 2023; Segbenya et al., 2023) and hinder the development of critical thinking skills, reduce human interaction and emotional connections, and amplify biases within the system (Nguyen et al., 2023). For example, Farrokhnia, Banihashem, Noroozi, and Wals (2024), in a SWOT analysis of ChatGPT, highlighted challenges with a lack of deep understanding, difficulty in evaluating the quality of responses, a risk of bias and discrimination, and declining higher-order cognitive skills. They also highlighted threats to higher education, including compromised academic integrity and increased plagiarism. Finally, in a comprehensive review, Ray (2023) explored ChatGPT's transformative role in scientific research, including data processing, hypothesis generation, collaboration, and public outreach, and suggests that addressing the ethical challenges of using ChatGPT in research requires balancing AI-driven innovation with human expertise.

2.3. Evolutions of the Technology Acceptance Model (TAM)

The original TAM is grounded in the Theory of Reasoned Action (TRA), proposed by Ajzen and Fishbein (1975), which predicts the attitudinal drivers of behavior across various domains. Davis (1989) stated, "TAM elucidates the determinants of technology acceptance, explaining behavior while aligning with theoretical and economic perspectives." The TAM has five constructs: perceived ease of use (PEU), perceived usefulness (PU), attitude towards use (ATU), behavioral intention (BI), and User Behavior (UB) and are considered the primary determinants for users concerning application and technology acceptance.

According to Davis (1989), PEU is the level at which an individual asserts that using a given technology will require less effort. PU is the level at which an individual believes their job performance will increase using a given technology. ATU is an individual's positive or negative attitude toward performing the intended behavior when applying a given system. BI is the level at which technology users have shaped a plan of intent to continue utilizing or not a particular technology with their future behavior. UB is the degree of usage application of a specific technology in terms of frequency (how often) and the measured volume (how much) when using a given technology by users.

Venkatesh and Davis (2000) expanded the original TAM into TAM 2 by adding variables subjective norm (SN), defined as "a person's perception that most people who are important to him think he should or should not perform the behavior in question." This construct was hypothesized to influence intention directly and indirectly through image and perceived usefulness. A combination of the predictors of the Theory of Planned Behavior (TPB) and TAM (C-TAM-TPB) added the variable of Attitude Towards Technology (ATU) and perceived Behavioral Control (Venkatesh et al., 2003; Ajzen, 1991). A Unified Theory of the Acceptance and Use of Technology (UTAUT) was also developed to combine various theories and iterations of the TAM (Venkatesh et al., 2003).

2.4. Utility of TAM in cross-disciplinary research

The TAM has been used to assess technology acceptance in various fields, including video gaming and family-life dynamics (Bassiouni et al., 2019), consumer attitudes toward online shopping chatbots, e-shopping tools and their adoption (Araújo & Casais, 2020; Ha & Stoel, 2009), internet banking (Yousafzai et al., 2010), online travel reviews, user-generated content (UGC) adoption (Assaker, 2020), mobile phone technology, automated road transport (Madigan et al., 2017), and healthcare/medicine (Lin & Yu, 2023; Yetisen et al., 2018). When TAM was adapted to test the most significant factors influencing a user's behavioral intention to use a mobile wallet, PEU and PU significantly affected the behavioral intention, further influencing the user's mobile wallet use (Singh & Sinha, 2020). Demoulin and Coussement (2020) observed that while PU consistently influenced technology adoption, the effect of PEU varied, particularly for text-mining tools.

A study by Teeroovengadum et al. (2017) assessed the factors that influence higher educators' adoption of Information and Communication Technology (ICT), and the results showed that the constructs PU and PEU had a significant influence on ICT use among educators. Similar studies have used TAM to examine the determinants of accepting online teaching and using Learning Management Systems (Luo et al., 2021; Wingo et al., 2017). Aliaño et al. (2019) found high levels of user behavior in utilizing mobile devices for learning, with the underlying TAM constructs having significant relationships. Strzelecki (2024) explored the factors driving students' acceptance of ChatGPT in higher education and found that behavioral intention exerted the most significant effect (0.424) on user behavior, with a model explaining 72.8% of the behavioral intention and 54.7% of the user behavior variance. TAM has also been used in studies with respondents from different cultures and geographical backgrounds (Al-Gahtani et al., 2007; Attuquayefio & Addo, 2014; Ko & Leem, 2021; Singh & Sinha, 2020; Tulinayo et al., 2018).

2.5. Limitations of TAM

As with any empirical model, TAM has limitations. Goodhue (2007) argues that the model focuses on the factors that make people utilize technology and blurs the focus on the impact of technology utilization on performance, implicitly suggesting that the more technology is utilized, the better the performance, which is not observed in practice. Venkatesh et al. (2007, 2012) also critique the simplicity of TAM and the lack of understanding of the antecedents of technology acceptance (perceived usefulness and perceived ease of use). Despite the noted limitations, we used the TAM because King and He (2006) maintain that it is theoretically resilient and has strong predictive power to assess individuals' intention to use technology. Lin and Yu (2023) further recommend incorporating new factors into TAM and applying them to diverse contexts using structural equation modeling methods. Finally, Luo et al. (2021) found that the TAM constructs PU, PEU, ATU, SN, BI, and UB explained relatively higher variances among respondents' data.

3. Method and materials

3.1. Research design

The researchers used a quantitative approach framed in a post-positivist worldview to evaluate how the TAM factors assess respondents' perceptions of AI ChatGPT and user behavior. This worldview is typically quantitative, focusing on the causes that influence outcomes. Creswell and Creswell (2017) posit that the process begins with theory, followed by data collection to either support or refute the theory. This approach is premised on rational considerations shaping knowledge, with researchers aiming to develop relevant, factual statements that explain or describe phenomena.

3.1.1. Survey development

We used an online and anonymous survey instrument to elicit respondents' perceptions on scale items related to TAM. The survey items for TAM factors were derived from Venkatesh et al. (2003) and Lin and Yu (2023). The items for ethical use (EU) were derived from Nguyen et al. (2023). The items for the student learning outcomes (SLO) and user behavior (UB) were obtained from the Students' Evaluation of Learning and Instructions (SELFI), which is a validated instrument used by the University of North Dakota (UND) for evaluating students' learning outcomes (UND, 2024). The final survey instrument had twenty-four (24) items (Likert scale; 1 = strongly disagree to 7 = strongly agree) related to TAM factors, all in English since all the universities conduct instructions in English. There were also five (5) UB items, four (4) SLO items, and six (6) items for EU. There were seven (7) demographic items and an open-ended item for additional comments. Table 1 provides examples of scale items.

3.1.2. Hypotheses

Drawing from existing literature, we hypothesized direct and

Table 1
Study construct scale item examples and sources.

Study Construct (TAM)	Example of Scale Item	Source
Perceived Usefulness (PU)	Using AI ChatGPT enhances the productivity of my scholarly work.	(Lin & Yu, 2023; Venkatesh et al., 2003)
Perceived Ease of Use (PEU)	My interaction with AI ChatGPT for academic/educational work is clear and understandable.	(Lin & Yu, 2023; Venkatesh et al., 2003)
Subjective Norms (SN)	The support from my professors or university in using AI ChatGPT is important to me.	(Lin & Yu, 2023; Venkatesh et al., 2003)
Attitude Towards Technology Use (ATU)	I have a generally favorable attitude toward using AI ChatGPT.	(Lin & Yu, 2023; Venkatesh et al., 2003)
Behavioral Intention (BI)	I intend to use AI ChatGPT for my scholarly work frequently.	(Lin & Yu, 2023; Venkatesh et al., 2003)
User Behavior (UB)	I regularly attend classes of professors who allow the use of AI ChatGPT in their courses.	(UND, 2024)
Student Learning Outcome (SLO)	AI ChatGPT use helps me develop in-depth knowledge of various physics topics.	(UND, 2024)
Ethical Use (EU)	The use of AI ChatGPT can lead to cheating and plagiarism in scholarly works.	Nguyen et al. (2023)

Note. The entire survey is attached as supplementary material.

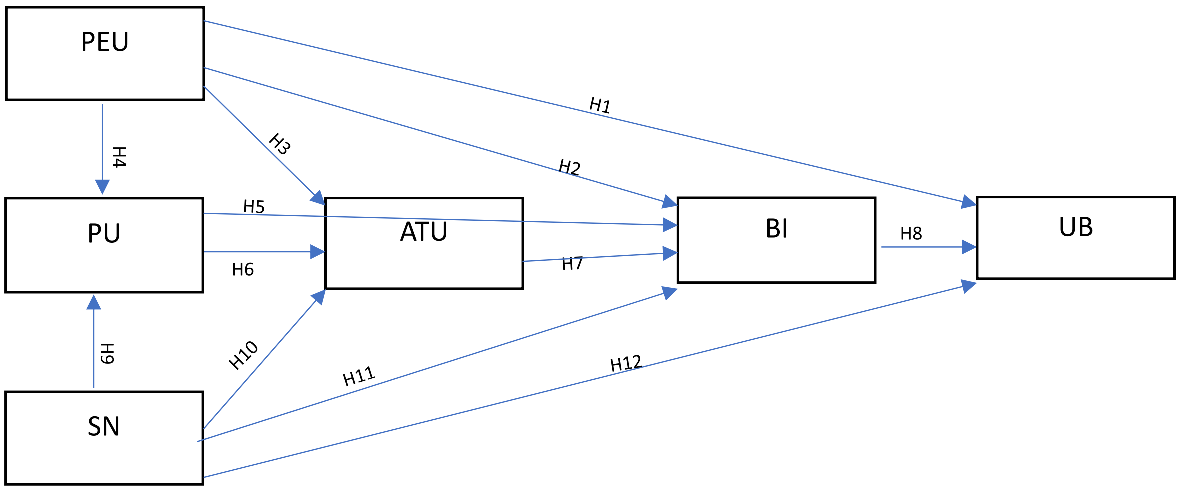

Fig. 1. A measurement model showing the hypothesized relationships between modified TAM factors.
Note: Adapted from (Davis, 1989; Venkatesh, 2003).

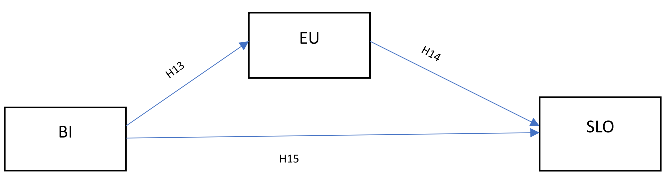

Fig. 2. Path Model showing the hypothesized relationships between BI, EU, and SLO.

indirect relationships among TAM constructs, user behavior, ethical use, and student learning outcomes. We also proposed and validated a measurement model assessed for fit using the Confirmatory Factor Analysis (CFA). Structural Equation Modeling (SEM) Path Analysis (PA) was used to evaluate the strength of relationships among the study variables. Another set of path analyses was used to assess the mediation effect of EU on the following relationships: BI and SLO and BI and UB. Fig. 1 shows the hypothesized measurement model for the TAM. Fig. 2 shows the pathways between the BI, EU, and SLO. Fig. 3 shows the pathways between BI, EU, and UB. Table 2 shows the hypotheses.

3.1.3. Sampling and survey administration

The sample for the study was purposefully drawn from a cross-section of undergraduate and graduate student populations enrolled in physics programs from four public universities, namely Stockton University in Galloway, New Jersey, USA, and the University of Ghana (UG) in Legon, Ghana. The other two universities were Kwame Nkrumah University of Science and Technology (KNUST) in Kumasi, Ghana, and Al-Hussein Bin Talal University in Ma'an, Jordan.

A convenience sample was used because the researchers were faculty members at the selected universities and acted as gatekeepers for easy access and to meet institutional review board requirements. After a Stockton University institutional review board approved the protocols for the study, an anonymous online survey instrument was created via a Qualtrics® institutional account.

The anonymous survey link was sent to the respondents through contact persons (faculty members) at the target physics departments who facilitated the dissemination of the link via emails and departmental listservs. The surveys included QR codes, which could be shared via phones and social media to facilitate easy distribution among the target respondents. Due to the international dissemination and varying semester schedules of the universities, data collection was staggered. The surveys for the University of Ghana were done first, followed by those for Stockton University, KNUST, and Al-Hussein Bin Talal University. The dissemination and collection period was eight weeks, from the first week of February 2024 to the first week of April 2024.

3.2. Preliminary data collection and analysis

At the end of an eight-week survey period, 804 responses were obtained (n = 804). Some respondents did not disclose their preference for some of the survey items (undisclosed). Compared to non-response, the response rate suggests minimal bias (Shih & Fan, 2009). The overall response rate was about 27 % (804 out of 3001). The details of the demographic and behavioral analysis of university participants, including distribution across institutions, gender, age groups, academic levels, and AI Chatbot usage frequency, are outlined in Table 3.

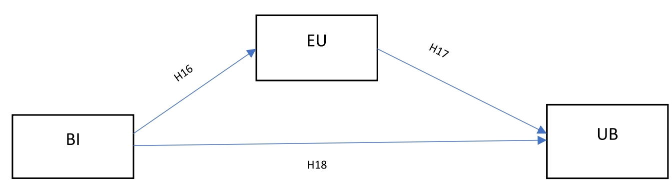

Fig. 3. Path Model showing the hypothesized relationships between BI, EU, and UB.

Table 2
Hypotheses of the relationships between the research constructs.

Number	Hypothesis
H1	PEU has a significant predictive relationship with UB
H2	PEU has a significant predictive relationship with BI
H3	PEU has a significant predictive relationship with ATU
H4	PEU has a significant predictive relationship with PU
H5	PU has a significant predictive relationship with BI
H6	PU has a significant predictive relationship with ATU
H7	ATU has a significant predictive relationship with BI
H8	BI has a significant predictive relationship with UB
H9	SN has a significant predictive relationship with PU
H10	SN has a significant predictive relationship with ATU
H11	SN has a significant predictive relationship with BI
H12	SN has a significant predictive relationship with UB
*H13	BI has a significant predictive relationship with EU
H14	EU has a significant predictive relationship with SLO
H15	BI has a significant predictive relationship with SLO
*H16	BI has a significant predictive relationship with EU
H17	EU has a significant predictive relationship with UB
H18	BI has a significant predictive relationship with UB
H19	EU significantly mediates the relationship between BI and SLO
H20	EU significantly mediates the relationship between BI and UB

Note. *H13 and *H16 are similar but are in different path analyses.

Table 3
Demographic and behavioral analysis of university participants: Distribution across institutions, gender, age groups, academic levels, and AI Chatbot usage frequency.

Distribution Type	Category	N	%
University	Stockton University, USA.	66	8.2
	Kwame Nkrumah University of Sc. & Tech. Kumasi, Ghana.	253	31.5
	University of Ghana. Legon, Ghana.	279	34.7
	Al-Hussein Bin Talal University, Ma'an, Jordan.	126	15.7
	Undisclosed	80	10
	Total	**804**	**100**
Gender	Male	407	50.6
	Female	309	38.4
	Third gender/Non-binary/ Prefer not to disclose	88	11
	Total	**804**	**100**
Age Group	18–22	595	74
	23–27	108	13.4
	28+	101	12.6
	Total	**804**	**100**
Academic Level	Undergraduate (First and Second Year)	411	51.1
	Undergraduate (Third and Fourth Year)	290	36.1
	Graduate (Masters and Doctoral)	103	12.8
	Total	**804**	**100**
Self-reported AI ChatGPT Usage Frequency	Never	200	24.9
	Sometimes	348	43.3
	About half of the time	64	8
	Often	90	11.2
	Always	22	2.7
	Undisclosed	80	9.9
	Total	**804**	**100**
Self-reported use of other Chatbots apart from ChatGPT in academic work	Yes	222	27.6
	No	496	61.7
	Undisclosed	86	10.7
	Total	**804**	**100**

Note. Percentages were rounded up to one decimal place to ensure brevity.

4. Results

4.1. Normality of data and descriptive statistics

We used IBM SPSS® Version 28 for descriptive and inferential computations as part of the preliminary analysis. The data was checked for normality to ensure that assumptions of linearity were not violated, and a visual inspection of histograms, N-N plots, and P-P plots was performed. No indications of abnormality were found, as the skewness and kurtosis values of the constructs were less than 3.000, the threshold Kline (2023) recommends for normality.

4.2. Confirmatory Factors Analysis (CFA) and structural model fit

Confirmatory Factors Analysis (CFA) was used to assess the fit of empirical data to the multi-dimensional model of all the constructs and their underlying items. The chi-square (χ^2) test is frequently assessed; however, it is sample size-dependent and can lead to rejection of the models with high sample sizes when significant (Kline, 2023). The root mean square error approximation (RMSEA) statistics are unaffected by sample size but can be influenced by model complexity, and a value less than 0.05 is better (Brown, 2015, pp. 91–94), and a value greater than 0.10 suggests problems with the model's fitness (Kline, 2023).

The Comparative fit index (CFI) can range between 0 and 1.0, with a value greater than or equal to 0.95, indicating a satisfactory fit (Kline, 2023). The Tucker-Lewis index (TLI) is a nonstandard fit index that may have values beyond the range of 0–1.0; however, it is preferable to have a value close to 1.0, and a value greater than 0.95 is good (Brown, 2015, pp. 91–94). The final statistics analyzed included the normed fit index (NFI) and the incremental fit index (IFI). NFI and IFI values should be greater than 0.90; otherwise, it indicates the need for model enhancements (Bentler & Bonett, 1980). Combining reported fit indices can help determine the optimal model fit (Hu & Bentler, 1999).

The average variances extracted (AVE) approach was used to determine convergent validity, which refers to how closely a new scale is related to other variables and measures of the same construct. Fornell and Larcker (1981) recommend a value greater than 0.50. The AVE values for all constructs were greater than the 0.50 threshold, suggesting acceptable convergent validity. Field (2018) and Hair et al. (2010) recommend a value of 0.70 or greater in determining acceptability reliability or consistency for survey items; all items had values greater than the 0.70 threshold. The instrument's discriminant validity was found acceptable by comparing the square root of the AVE for constructs to the correlation coefficients for each variable. The square roots of the AVE on the diagonal line were greater than all other correlations in the corresponding columns and rows, indicating that the covariates could be significantly distinguished. Table 4 shows the descriptive statistics of the study variables, reliability test, convergent validity test, model fit indices, and discriminant validity test.

4.3. Analysis and findings of research questions

4.3.1. Research question one

What are the strengths of relationships among TAM factors assessing respondents' perceptions of ChatGPT and user behavior?

The first phase of assessing the strength of relationships among the TAM factors involved validating a structural equation model (SEM) that mapped exogenous variables (PEU, SN) to endogenous variables (PU, ATU, BI, and UB). The validity of the TAM was assessed through goodness-of-fit indices and squared multiple correlations derived from maximum-likelihood estimations using IBM SPSS® AMOS 28 Graphics. Bootstrapping is a non-parametric method based on resampling with replacement, which is done many times, e.g., 5000 times (Bollen & Stine, 1990; Shrout & Bolger, 2002) and was used in this analysis. According to Hayes (2017), the indirect effect can be computed from these samples, and a sampling distribution is empirically generated. Hayes (2017) further suggests that because the mean of the bootstrapped distribution will not exactly equal the indirect effect, a correction for bias can be made, and a confidence interval, p-value, or standard error can be determined with the distribution. The confidence interval was computed and checked to determine if a zero value was in the interval. A non-zero value in the interval suggests that the indirect effect differs from zero (Hayes, 2017).

The SEM/PA measurement model demonstrated a good fit for the data, as evidenced by the fit indices. Even though the path between PU and BI was insignificant, all the others were statistically significant and supported the hypothesized relationships between the TAM constructs. The measurement model had significant explanatory powers measured by the squared multiple correlations (SMC) values of the endogenous variables (PU, ATU, BI, and UB). The measurement model explained about 50.4% variance of PU, 54.9% of ATU, 59.3% of BI, and 41.3% of UB. For the exogenous variables, the path coefficients measured the effect sizes (Kline, 2023). The three paths with the largest effect sizes were PEU to PU, ATU to BI, and SN to UB. The path from PEU to UB exhibited the lowest effect size. The maximum likelihood estimates, standard error (SE), critical ratio (CR), p-values, standardized regression weight, hypothesis testing, squared multiple correlations, and hypothesized model fit indices are shown in Table 5.

Table 4
Number of scale items, Mean, Standard Error (SE), Cronbach's Alpha (α), Composite Reliability (C.R.), Average Variances Extracted (AVE), and Model Fit Indices.

Construct	Items	Mean	SE	α	C.R.	AVE
PU	4	5.05	0.045	0.93	0.93	0.75
PEU	3	5.06	0.044	0.89	0.89	0.73
SN	3	3.99	0.048	0.85	0.85	0.58
ATU	4	5.17	0.039	0.88	0.88	0.65
BI	3	4.71	0.048	0.91	0.91	0.77
SLO	4	4.94	0.040	0.91	0.90	0.70
UB	4	4.41	0.047	0.89	0.87	0.64
EU	4	4.89	0.039	0.87	0.86	0.61

Model	**Structural Model Fit Indices**
CFA	$\chi^2 = 763.585$, $p < 0.001$, PCMIN/DF = 4.062 NFI = 0.930, RFI = 0.910, LFI = 0.950, TLI = 0.930, CFI = 0 0.950 RMSEA = 0. 060 (0.057–0.066)

Discriminant Validity

	PU	PEU	SN	ATU	BI	SLO	UB	EU
PU	**0.866**							
PEU	0.690**	**0.854**						
SN	0.499**	0.519**	**0.761**					
ATU	0.695**	0.616**	0.537**	**0.806**				
BI	0.586**	0.557**	0.531**	0.750**	**0.877**			
SLO	0.607**	0.586**	0.524**	0.712**	0.691**	**0.836**		
UB	0.437**	0.516**	0.554**	0.510**	0.527**	0.598**	**0.800**	
EU	−0.028	−0.043	−0.178**	−0.035	−0.102**	−0.072*	−0.217**	**0.781**

Note. The square roots of AVE are in bold on the diagonal. ***p* is significant at the 0.01 level (2-tailed). **p* is significant at the 0.05 level (2-tailed). All constructs had AVE values ≥ 0.50 threshold recommended by Fornell and Larcker (1981) for evidence of convergent validity.

To assess the mediation role of some construct in the hypothesized model, the Hayes PROCESS© for SPSS 28 Version 4 was used. The 95% bootstrap confidence interval (BCI) with 5000 samples was used. The model summary and effect size in the form of R^2 are reported. A significant standardized indirect effect (Std. Ind. Eff.) and a non-zero value between the lower and upper limits of the 95% BCI (LLCI – ULCI) were used to infer mediation based on the suggestion that the indirect effect is significantly larger than 0 (Biesanz et al., 2010; Fritz & MacKinnon, 2007; Hayes, 2017). Six different mediation analyses were done, and the results suggested that the highest mediation occurred when ATU mediated the path of PEU to BI. The lowest mediation occurred when BI mediated the path from SN to UB. Details are highlighted in Table 6. Fig. 4 shows the SEM/PA measurement model with regression weights and SMC values.

Table 5
Results of the maximum likelihood estimates, standard error (SE), critical ratio (CR), P-values, standardized regression weight **(β)**, hypothesis testing, squared multiple correlations (SMC), and hypothesized model fit indices.

Number	Path	S.E.	C.R.	*P*	*β*	Hypothesis
H1	UB ← PEU	0.037	6.457	***	0.222	Supported
H2	BI ← PEU	0.036	2.711	0.007	0.090	Supported
H3	ATU ← PEU	0.030	5.561	***	0.190	Supported
H4	PU ← PEU	0.030	20.244	***	0.590	Supported
H5	BI ← PU	0.038	1.223	0.221	0.044	Not Supported
H6	ATU ← PU	0.029	13.580	***	0.459	Supported
H7	BI ← ATU	0.042	17.407	***	0.585	Supported
H8	UB ← BI	0.034	6.836	***	0.237	Supported
H9	PU ← SN	0.027	6.623	***	0.193	Supported
H10	ATU ← SN	0.023	7.347	***	0.210	Supported
H11	BI ← SN	0.028	5.276	***	0.148	Supported
H12	UB ← SN	0.033	9.252	***	0.312	Supported

Construct	SMC	Hypothesized Model Fit Indices
PU	0.504	$\chi^2 = 4.323$, $p = 0.115$, PCMIN/DF = 2.161
ATU	0.549	NFI = 0.998, RFI = 0.982, IFI = 0.999, TLI = 0.991
BI	0.593	CFI = 0 0.998, RMSEA = 0.038 (0.000–0.088)
UB	0.413	

4.3.2. Research question two

How does the ethical use of ChatGPT influence the relationship between behavioral intentions and students' learning outcomes among respondents?

We used IBM AMOS® 26 to check the mediation role of EU on the relationship between BI and SLO. The Hayes PROCESS® version 4 was used to confirm the model. The number of bootstrap samples for 95% BCI was 5000. The model summary was [MSE = 0.67, F (2, 796) = 364.04, p = 0.000, and a medium effect size (R-sq = 0.478)]. The standardized direct effect of BI on EU was significant (β = −0.08, p = 0.022), while the standardized direct effect of EU on SLO was not significant. The standardized indirect effect of BI on SLO mediated by EU was 0.00. This suggests that EU did not significantly mediate the relationship between BI and SLO. Table 8 shows the regression weights, t-statistics, standard error, p-values, and BI, EU, and SLO relationship hypothesis statements.

Table 6
Results of mediation analyses using the Hayes PROCESS© Version 4 and bootstrapping.

Path	Mediator	F (2, 796)	*p*	R^2	Std. Ind. Eff. (SE)	LLCI - ULCI	Mediation
ATU ← PEU	PU	427.827	***	0.518	0.356 (0.038)	0.283–0.434	YES
BI ← PEU	ATU	543.464	***	0.577	0.404 (0.027)	0.349–0.457	YES
UB ← PEU	BI	214.074	***	0.350	0.193 (0 0.023)	0.150–0.238	YES
ATU ← SN	PU	450.787	***	0.531	0.284 (0.027)	0.230–0.337	YES
BI ← SN	ATU	562.427	***	0.586	0.351 (0.023)	0.307–0 0.395	YES
UB ← SN	BI	214.074	***	0.382	0.172 (0.021)	0.138–0.213	YES

Note: ****p* < 0.001.

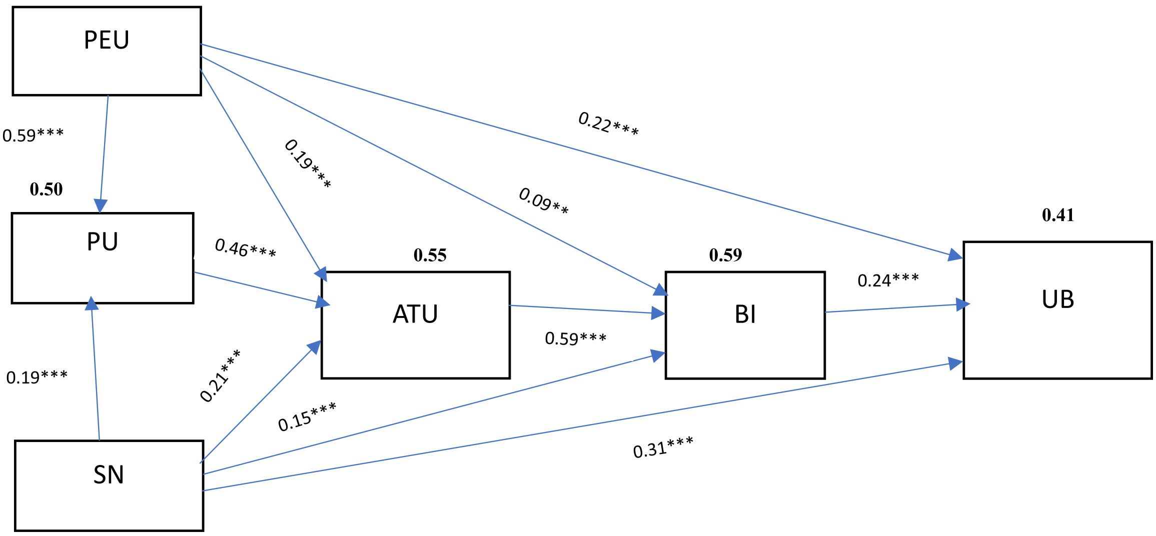

Fig. 4. Final Hypothesized Measurement Model
Note. ***p < 0.001,**p < 0.001, Non-significant PU – BI path removed for clarity.

Table 7
Path Relationships for Hypotheses H13 to H18 and their respective regression weights (β), t-statistics, standard error (SE), probability value (p), hypothesis test statement, mediation analysis for H19 to H20, and SMC.

Number	Path	*β*	*t-statistic*	*S.E*	*p*	Hypothesis
H13	EU ← BI	−0.08	−2.281	0.029	0.023	Supported
H14	SLO ← EU	0.00	0.073	0.021	0.941	Not Supported
H15	SLO ← BI	0.69	26.901	0.214	0.000	Supported
H16	EU ← BI	−0.08	−2.281	0.029	0.023	Supported
H17	UB ← EU	−0.16	−5.300	0.035	0.000	Supported
H18	UB ← BI	0.51	17.313	0.029	0.000	Supported

Number	Path	Std. Ind. Eff.	LLCI	ULCI	Mediation
H19	SLO ← EU ← BI	0.000	−0.004	0.007	No
H20	UB ← EU ← BI	0.013	−0.001	0.031	Yes

Construct	**SMC**
EU	0.01
SLO	0.48
UB	0.30

4.3.3. *Research question three*

How does the ethical use of ChatGPT influence the relationship between behavioral intentions and user behavior of respondents?

We used IBM AMOS® 26 to check the models for the mediation role of EU on the relationship between BI and UB, and the Hayes PROCESS® version 4 was used to confirm the model. The number of bootstrap samples for 95% BCI was 5000. The model summary was [MSE = 1.24, F (2, 796) = 172.44, *p* = 0.0000, with a small to medium effect size ((R-sq = 0.302)]. The standardized indirect effect suggests a significant mediation of EU on the relationship between BI and UB, albeit small. Table 7 shows the regression weights, *t*-statistics, standard error, *p*-values, hypothesis statements of the relationships between BI, EU, and UB, and squared multiple correlations for EU, SLO, and UB.

4.3.4. *Research question four*

How do behavioral intentions, user behavior, and student learning outcomes relate to the frequency of ChatGPT use in academic work?

We used multiple regression to validate the use of ChatGPT among respondents and to determine the predictive relationships between ChatGPT acceptance outcomes and self-reported use frequency (FREQ). The results suggest that the predictive model was statistically significant [R = 0.416, SE = 0.0962, F (3, 720) = 50.220, p < 0.001], but the effect size was relatively small (R-sq = 0.17). The regression coefficient showed significant positive predictive relationships between predictors UB, SLO, and BI with an outcome variable of self-reported frequency of ChatGPT use in academic work (FREQ). The predictors can provide meaningful insights on self-reported use frequency despite the small variance explained (17%). We interpreted the model because Ozili (2023) suggests that most social science research modeling aims not to predict human behavior but to assess whether specific predictors significantly affect the dependent variable. Therefore, a low R-square of at least 0.1 (or 10 percent) is acceptable on the condition that some or most of the predictors or explanatory variables are statistically significant. Table 8 shows the correlations of variables and the regression model summary.

Table 8
Correlation and Regression Model of predictors BI, UB, SLO, and outcome variable FREQ.

	BI	UB	SLO	FREQ
BI	1	0.501	0.642***	0.291**
UB	0.501***	1	0.677***	0.420***
SLO	0.642***	0.677***	1	0.420***
FREQ	0.291**	0.420***	0.420***	1

Model Summary

Variables	B	SE	β	t	p	LLCI	ULCI
Constant	0.309	0.162	–	1.903	0.057	−0.010	0.628
UB	0.146	0.035	0.188	4.191	<0.001	0.078	0.215
SLO	0.121	0.047	0.132	2.586	0.010	0.029	0.214
BI	0.125	0.037	0.162	3.366	<0.001	0.052	0.199

Note. ****p* < 0.000 and ***p* < 0.001. Outcome is FREQ.

4.3.5. *Research question five*

What are the demographic differences in perceptions of TAM constructs (BI, UB) and student learning outcomes (SLO)?

We used a one-way analysis of variance (ANOVA) to determine if significant differences existed in the perceptions of the three endogenous factors among demographic variables (university, academic level, gender, and age groups). When the assumption of homogeneity of variances was violated or sample sizes were unequal, the Games-Howell test was used for post hoc analysis with a 95% percentile bootstrap confidence interval (BCI).

4.3.5.1. *Universities.* For the university group, there was some statistical significance in the mean scores for all three endogenous variables. There were significant differences among the universities for UB [$F(3, 720) = 63.686$, $p < 0.001$, $\eta^2 = 0.021$ with 95% BCI (0.158–0.257)]. Al-Hussein University had the highest mean score [M = 5.23, SE = 0.086, 95% BCI (5.041–5.381)] and was significantly different from KNUST [M = 4.87, SE = 0.003, 95% BCI (4.720–5.026)], Stockton University [M = 3.83, SE = 0.167, 95% BCI (3.507–4.192)] and UG which had the lowest score [M = 3.76, SE = 0.765, 95% BCI (3.507–4.192)]. There were no significant differences in Stockton's mean scores or UG's.

There were significant differences in scores among the universities for SLO [$F(3, 720) = 40.994$, $p < 0.001$, $\eta^2 = 0.146$ with 95% BCI (0.099–0.190)]. Al-Hussein University had the highest mean score [M = 5.40, SE = 0.069, 95% BCI (5.272–5.539)] and was significantly different from UG [M = 4.55, SE = 0.067, 95% BCI (4.418–4.680)] and Stockton University [M = 4.36, SE = 0.184, 95% BCI (3.980–4.730)] which had the lowest score. There were no significant differences between Al-Hussein and KNUST [M = 5.38, SE = 0.060, 95% BCI (5.250–5.490)], though there were significant differences between Stockton and KNUST. There were also significant differences between KNUST and UG.

There were significant differences in scores among the universities for BI [$F(3, 720) = 35.692$, $p < 0.001$, $\eta^2 = 0.129$ with 95% BCI (0.085–0.173)]. Al-Hussein University had the highest mean score [M = 5.41, SE = 0.079, 95% BCI (5.246–5.550)] and was significantly different from KNUST [M = 5.08, SE = 0.074, 95% BCI (4.948–5.230)], UG [M = 4.28, SE = 0.083, 95% BCI (4.114–4.436)] and Stockton University [M = 4.08, SE = 0.217, 95% BCI (3.667–4.518)] which had the lowest score. There were no significant differences between Stockton and UG, though there were significant differences between Stockton and KNUST. There were also significant differences between KNUST and UG.

4.3.5.2. Academic levels. There were significant differences in mean scores among the academic levels for UB [$F(2, 796) = 22.522$, $p < 0.001$, $\eta^2 = 0.054$]. The senior undergraduates (third and fourth years) had the highest mean score [M = 4.78, SE = 0.078, 95% BCI (4.613–4.922)], which was significantly different from that of junior undergraduates (first and second years) [M = 4.11, SE = 0.068, 95% BCI (3.986–4.251)] who had the lowest score. There was also a significant difference between the scores of junior undergraduate and graduate students [M = 4.55, SE = 0.110, 95% BCI (4.336–4.777)]. There were no differences in the scores of senior undergraduates and graduate students.

There were significant differences in scores among the academic levels for SLO [$F(2, 796) = 15.547$, $p < 0.001$, $\eta^2 = 0.038$]. Senior undergraduate students had the highest mean score [M = 5.19, SE = 0.068, 95% BCI (5.051–5.315)] and were significantly different from graduate students [M = 4.83, SE = 0.097, 95% BCI (4.636–5.020)] and junior undergraduate students [M = 4.79, SE = 0.057, 95% BCI (4.678–4.915)] with the lowest score.

There were significant differences in scores among the academic levels for BI [$F(2, 796) = 15.547$, $p < 0.001$, $\eta^2 = 0.038$]. The senior undergraduate students had the highest mean score [M = 5.05, SE = 0.082, 95% BCI (4.875–5.199)] and were significantly different from graduate students [M = 4.66, SE = 0.126, 95% BCI (4.400–4.908)] and junior undergraduate students [M = 4.48, SE = 0.066, 95% BCI (4.350–4.619)] with the lowest score.

4.3.5.3. Gender. There were significant differences in mean scores among genders for user behavior [$F(2, 796) = 6.499$, $p = 0.002$, $\eta^2 = 0.016$]. Males had the highest mean score [M = 4.56, SE = 0.067, 95% BCI (4.430–4.692)], which was significantly different from that of females [M = 4.20, SE = 0.077, 95% BCI (4.052–4.352)] who had the lowest score. There was no significant difference between either males or females and third/non-binary/prefer not to disclose [M = 4.45, SE = 0.118, 95% BCI (4.210–4.683)].

There were significant differences in scores among genders for SLO [$F(2, 796) = 7.702$, $p < 0.001$, $\eta^2 = 0.019$]. Males had the highest mean score [M = 5.01, SE = 0.056, 95% BCI (4.978–5.198)] and were significantly different from females [M = 4.82, SE = 0.066, 95% BCI (4.690–4.494)] and third/non-binary/prefer not to disclose [M = 4.67, SE = 0.097, 95% BCI (4.480–4.807)] with the lowest score.

For behavioral intention, there were significant differences in scores among the genders [$F(2, 796) = 6.383$, $p = 0.002$, $\eta^2 = 0.019$]. Again, males had the highest mean score [M = 4.87, SE = 0.064, 95% BCI (4.746–4.998)] and were significantly different from females [M = 4.55, SE = 0.881, 95% BCI (4.389–4.710)] and third/non-binary/prefer not to disclose [M = 4.47, SE = 0.140, 95% BCI (4.194–4.753)] with the lowest score.

4.3.5.4. Age group. For the UB construct, there were significant differences in mean scores among age groups [$F(2, 796) = 4.898$, $p = 0.008$, $\eta^2 = 0.012$]. The 23–27 group had the highest mean score [M = 4.78, SE = 0.127, 95% BCI (4.524–5.028)], which was significantly different from that of the 18–22 group [M = 4.34, SE = 0.055, 95% BCI (4.234–4.451)] with the lowest score. However, the 23–27 group score was not significantly different from that of the 28+ group [M = 4.42, SE = 0.119, 95% BCI (4.180–4.656)].

There were significant differences in mean scores among age groups for SLO [$F(2, 796) = 10.414$, $p < 0.001$, $\eta^2 = 0.026$]. The 23–27 group had the highest mean score [M = 5.36, SE = 0.095, 95% BCI (5.165–5.554)], which was significantly different from that of the 18–22 group [M = 4.91, SE = 0.047, 95% BCI (4.814–4.999)] and the 28+ group [M = 4.69, SE = 0.101, 95% BCI (4.484–4.888)] who had the lowest score. Finally, there were significant differences in mean scores among age groups for BI [$F(2, 796) = 4.440$, $p = 0.012$, $\eta^2 = 0.011$]. The 23–27 group had the highest mean score [M = 5.04, SE = 0.129, 95% BCI (4.780–5.293)] which was significantly different from that of the 18–22 group [M = 4.68, SE = 0.055, 95% BCI (4.568–4.787)] and the 28+ group [M = 4.50, SE = 0.131, 95% BCI (4.180–4.656)] who had the lowest score.

5. Discussions and conclusion

5.1. Model utility and hypotheses

The results show that the hypothesized model, developed from the original TAM to assess AI ChatGPT use in collegiate physics education, significantly explained a substantial percentage of the variances observed in the endogenous variables (PU, ATU, BI, and UB). The hypothesized model accounted for approximately 50.4% of the variance of PU, 54.9% in ATU, 59.3% in BI, and 41.3% in UB. These findings demonstrate the robustness and applicability of the TAM and its extensions in predicting technology use across various disciplines, contexts, and geographical regions. The results demonstrate TAM's utility ability to fit data from multi-cultural and cross-institutional respondents. Our findings align with previous studies, such as those of Wingo et al. (2017) and Luo et al. (2021), demonstrating TAM's robustness and variants.

The findings suggest a significant relationship between all the hypothesized paths among the constructs except the direct relationship between perceived usefulness and behavioral intention. However, the exception differs from Davis (1989), who posits that perceived usefulness significantly influences behavioral intention to use technology. Davis asserts that when individuals consider technology useful, they can create a positive BI towards using technology. Eventually, this positive BI of users towards a given technology defines the actual use of such technology. Interestingly, the results were consistent with the insignificant findings reported by Lin and Yu (2023) for digital reading tools, as well as by Wang et al. (2022) and Deng and Yu (2023) for other educational technologies.

A possible explanation for this phenomenon is that despite Chatbot's "perceived usefulness" for scholarly purposes, students' behavioral intentions depend on whether they can easily use the tools. For example, the educational environments in Ghana, Jordan, and the U.S. differ significantly in technological infrastructure and readiness for technology integration. In Ghana, limited access to reliable internet, affordable computing resources, and a lower awareness level of AI tools/software and its impact on making informed decisions for use in scholarly work may dilute the impact of perceived usefulness on behavioral intentions, as suggested by Segbenya et al. (2023). It is plausible that PU might only influence BI indirectly through factors like institutional support and national technological infrastructure development, as suggested by Gyamfi et al., 2022.

Behavioral intent for ChatGPT use may be more likely in U.S. colleges, where access to affordable computing resources and the internet is better. However, concerns about over-reliance on ChatGPT and its impact on critical thinking skills might still create an indirect pathway, as observed by Segbenya et al. (2023). Additionally, collegiate physics as a discipline demands rigorous logical reasoning, and some educators may view ChatGPT as a potential primer that could undermine the development of these skills. This skepticism could adversely mediate the adoption process, even when usefulness is acknowledged.

In Ghana, using traditional teaching approaches and the influential role of instructors as primary sources of knowledge might impact the integration of ChatGPT into the learning process. Students and faculty might rely more heavily on social cues, such as peer acceptance or institutional endorsement, before developing the intent to use the technology. This could mediate the PU-BI relationship. In contrast, in Jordan and the U.S, where self-directed learning and AI technological experimentation are encouraged (Al Najdawi et al., 2024; U.S. Department of Education, 2023), the perception of ChatGPT's usefulness might more directly translate to the intention to use, as suggested by Crompton and Burke (2023).

Institutional policies on AI technology use can impact PU and BI. Policies on technology training and literacy, ethical concerns (plagiarism, over-reliance, informed consent, privacy breaches, biased data assumptions, fairness, and accountability) with ChatGPT can frame the behavioral intentions of users despite the acknowledgment of its perceived usefulness, as suggested by researchers such as Sacharidis et al. (2020), Cotton et al. (2023), Dehouche (2021) and Kumar et al. (2024). Institutional policies can also impact trust or confidence in ChatGPT's use, especially in collegiate physics education, where precision and correctness are paramount when seeking explanations or solving problems.

It is plausible that some participants find ChatGPT context-dependent and valuable only for specific tasks in a physics curriculum. Students may find it helpful for literature reviews, bibliographical searches, and computational analysis. However, ChatGPT may not be functional for scenario-based practical laboratory assignments. This perspective is supported by Maheshwari (2024), who found that students' inclination to adopt ChatGPT was more influenced by their perception of its user-friendliness (PEU) than the perceived usefulness of the tool.

There may also be complexities and learning curves inherent in using ChatGPT for some students who may be challenged with mastering all its functionalities. This can adversely influence their intention to use it. Finally, variations in how participants from different countries interpreted survey items might have influenced the observed relationships. For example, respondents might interpret "usefulness" in varying ways—some may focus on efficiency, while others may consider its impact on learning outcomes.

Our study's weak predictive relationship between SN and BI contrasts with that of Davis (1989), who found no significant relationship between the construct and suggested that some technological applications are individualized for personal benefit, and social influence may not necessarily motivate the intention to use them despite top management support. Ajzen (1991), in the Theory of Planned Behavior (TPB), suggests a possible reason for the inconsistencies in the significance between SN and BI by stating that some elements of SN are already present in the desirability of undertaking a particular behavior and intentions are heavily influenced by attitudes and perceived behavioral control.

Financial constraints may also limit some respondents' ability to purchase internet data and access ChatGPT in a developing economy like Ghana. That can impact the intention to use ChatGPT despite being nudged by peers and faculty members. Also, due to ethical concerns, some peers and professors can dissuade respondents from using ChatGPT. The net effect can be a weak predictive relationship between SN and BI among respondents.

From a cross-cultural setting, Chang-Dae et al. (2015) suggest that individuals from collectivist-oriented cultures may experience stronger social pressure from influential peers and are more willing to comply with their opinions. On the other hand, individuals born and raised in predominantly individualistic countries may have stronger attitudes toward certain behaviors. They may pay less attention to what other people think or do. As Jeffy et al. (2024) suggested this could explain the differences in perceptions of the link between SN and BI in a collectivistic culture like Ghana and Jordan and an individualistic culture like the U.S. Invariably, social influences, trust, or facilitating conditions can also impact the link between SN and BI (Menon & Shilpa, 2023).

5.2. *Institutional perspectives and influence*

From an institutional and organizational perspective, the University of Ghana and Al Hussein University strongly encouraged synchronous and asynchronous learning after the COVID-19 pandemic and the adoption of various online technological learning tools. This could have led to a change in the way students think about technology use. It is plausible that even though AI learning tools may be complex for students at the undergraduate level 100, as they progress to higher levels, they become more comfortable using these tools, including ChatGPT.

The significant mediation role of ATU between BI and UB suggests that respondents' attitudes toward ChatGPT can positively influence their intentions to use it, as found in previous studies by Wang et al. (2022), Deng and Yu (2023), and Lin and Yu (2023). Our finding of a strong relationship between BI and UB is similar to Ajzen (1991) and Venkatesh and Davis (2000), who suggest BI and non-motivational factors such as the availability of necessary opportunities, resources, and abilities, environmental factors, and even the interactions between motivation and ability factors determine actual user behavior.

Perceived usefulness significantly mediated the relationship between perceived ease of use and attitude towards technology. This may be because the perceived ease of using ChatGPT impacts attitudes towards use, which can be enhanced when the user assesses the functional value and relates it to whether they have the requisite skillset to apply it in a task. Attitude towards technology significantly mediated the relationship between PEU and BI.

This finding supports that of Feng et al. (2021), who found a strong effect of ATU on BI. The results suggest that a positive attitude is a good indication of behavioral intentions. PU mediated the relationship between SN and ATU, similar to Lin and Yu (2023) and Raygan and Moradkhani (2022) findings. This finding suggests that students can develop a positive attitude towards using ChatGPT and find it helpful to their academic achievements if professors, peers, and teaching staff recommend using them and stress their benefits to academic learning outcomes.

Feng et al. (2021) further found that the indirect effects (as well as the total effects) of the variables PEU on behavioral intentions are much lower than their direct effects on attitude toward technology use. This finding also implies that the PEU is an important determinant of ATU compared to BI. Attitudes toward technology use mediate the effects of PU and PEU on behavioral intentions, and cultivating a positive attitude is crucial to BI.

We also found that ATU significantly mediated the relationship between SN and BI, while PU mediated SN and ATU. These findings suggest that even with the influential role of the social networks of peers, professors, and college administrators in framing intentions to use ChatGPT, the inherent attitude towards this technology developed by the users significantly explains that relationship. These findings support that of Attuquayefio and Addo (2014), who suggest that institutional support and provision of a positive technological learning environment with easy access can build a positive attitude among college students, shape the intention to use AI technology and lead to enhanced use for learning and research. These findings also suggest that when students appreciate ChatGPT's value and create a positive attitude toward their use, they can influence their colleagues to use them.

Our findings also align with Teo (2010) and Buabeng-Andoh and Baah (2020), who found that SN significantly affected BI using technology when ATU mediated their relationship. The finding also suggests that there can be situations where respondents' intention to use ChatGPT in response to social pressure may not always be primed by potential gains or a need for compliance (Graf-Vlachy et al., 2018).

However, the seemingly strong direct relationship between SN and UB can be explained by the idea that even though TAM focuses on informational influence (learning from others), other factors, such as normative influence (feeling pressure to conform) and self-identification (wanting to belong to a group that uses ChatGPT) can be impactful (Lee et al., 2006). Finally, the results of this study validate the traditional TAM regarding its ability to assess students' technology acceptance and use, similar to those of Luo et al. (2021), who suggested that the traditional TAM can explain how PU, PEU, and ATU can influence the BI and UB of digital academic reading tools.

5.3. Ethical use concerns

Interestingly, ethical use concerns did not significantly mediate the relationship between behavioral intention and student learning outcomes. We surmise that some respondents may prioritize the perceived benefits of ChatGPT for their learning, even if they have some ethical concerns. They might be willing to overlook these concerns if they believe the tool can significantly enhance their academic performance, as Ko and Leem (2021) suggested.

It is important to note that ethical concerns significantly mediated the relationship between behavioral intention and user behaviors, albeit negatively. The survey items were designed to elicit responses on how ethical concerns negatively impact perceptions of using ChatGPT in academic work. This suggests that higher agreement with these concerns adversely influences the intention to use and the actual use of technology. The findings suggest that respondents with significant ethical use concerns, such as privacy issues, might be less likely to use ChatGPT, as found in a previous study by Parsons (2021). It is also plausible that behavioral intention to use ChatGPT for scholarly activities may be adversely influenced by concerns with the accuracy and transparency of information, as suggested by Eke (2023) and Farazouli et al. (2024).

We reiterate the policy recommendations by Segbenya et al. (2023), which suggest training students in AI Chatbot ethics and implementing transparent policies that outline allowable levels of fair use and similarity checks to minimize the abuse and overreliance on AI Chatbot software among students. University administrators can establish AI tracking detectors to check plagiarism, but students should be aware of such actions. Also, data privacy concerns, including potential misuse of student data by AI systems, call for strict adherence to privacy frameworks.

5.4. Demographic variations

We determined the correlations between frequency of use and user behavior and its impact on student learning outcomes. Unsurprisingly, frequency of use strongly correlated with UB and SLO. Despite the small effect size of the regression model, UB and BI emerged as the strongest predictors of use frequency, suggesting that frequent use of the technology was linked to BI and could indicate actual behavior. Also, consistent use of technology can reinforce its value and translate it into actual user behavior and habit formation. Some respondents may also be learning more about the technology through constant use, which makes them more comfortable with its functionalities and unearthing more potential benefits.

Among the universities, Al-Hussein had the highest user behavior, followed by KNUST, UG, and Stockton. The differences were statistically significant. Institutional culture on AI technology acceptance and use can explain this finding. Using documentary analysis and first-hand information from each researcher about current technology policies in their institutions, we found that each university had different institutional policies on generative AI, impacting ChatGPT use.

Al-Hussein University has an institutional policy of providing internet connectivity and laptops to students to improve their access to AI technology for learning and a formal ChatGPT policy for students and professors (Al-Hussein Bin Talal University, 2024). During the data collection period, UG amended its policy on academic integrity, where AI or associated technologies compromising the authenticity of academic output will be deemed unacceptable (Ghcampus.com, 2024).

Despite some sensitization drive to curb the use of generative AI for academic work, KNUST did not have a formal policy on generative AI use in academic work (KNUST E-learning Centre, 2023). In contrast, Stockton had a voluntary generative AI guide for faculty (Stockton University, 2024). It could encourage some professors to discourage its use in class and impose strict penalties for using ChatGPT for class tests or final examinations. These reasons can account for the significant differences in user behaviors observed. Other factors, such as the effects of socioeconomic status on the availability of AI resources, cannot be discounted.

Stein et al. (2024) suggest an association between personality traits and cultural attitudes toward using AI technology. Their findings suggested that personality traits are also anchored in perceptions of trust in cultures or societies with a higher post-factual conspiracy theory mentality. Strong expression of skepticism about governments and organizations, as well as related news coverage on perceived sinister threats of AI technologies by people, negatively affects their attitudes and intentions to use AI technology. As observed in Al-Hussien University, a sociocultural system that hinges on trust in public institutions minimizes skepticism toward using AI technology provided by public entities. On the contrary, a recent surge in disinformation about covert government manipulation of AI technology and other conspiracy theories in the U.S. and China, to name a few, could be a factor in the lack of trust in using AI technologies in higher education (Ryan-Mosley, 2023).

Respondents from Al-Hussein University had the highest mean scores for student learning outcomes. This could be attributed to the institutional and curriculum focus, which requires students to demonstrate knowledge and skills in using AI technology for physics research and online curation of scholarly materials. An emphasis on AI literacy as an SLO within the curriculum design and syllabi at Al-Hussien can significantly influence respondents' perceptions of ChatGPT use and SLO. KNUST and UG had significantly different scores on SLO, with notably high ChatGPT user behavior among respondents from KNUST and significant positive impacts on SLO. KNUST focuses more on STEM-based programs, and it is plausible that respondents find using AI tools helps attain SLO compared to their counterparts in UG, which had some restrictive AI use policies that can adversely affect its value in meeting SLO.

Stockton University had the lowest scores in UB and SLO among the four institutions. Due to the discretionary guidance on AI use, some physics faculty members limit the use of generative AI in their courses to prevent cheating and unethical use. This may result in low ChatGPT user behavior among students as its value may not be important from an SLO perspective. Despite this, the behavioral intention scores were relatively high, suggesting that there is potential for increased ChatGPT use if there are definitive institutional policies and encouragement from professors.

Regarding academic levels, senior undergraduates (third and fourth years) had the highest mean score for UB, significantly higher than junior undergraduates (first and second year), who scored the lowest. There was also a significant difference between the scores of junior undergraduate and graduate students. Leong et al. (2018) found that academic experience negatively predicts students' acceptance and use of digital academic reading tools on computers. It is likely that participants with academic experience using traditional media and academic resources, such as printed books and papers, are unwilling to switch to AI tools such as ChatGPT for academic purposes, as Lin and Yu (2023) suggested.

Deng and Yu (2023) also suggest that some graduate students may still search for scholarly materials and references through printed text instead of using ChatGPT based on their undergraduate experiences, which did not require much use of AI tools such as ChatGPT. Interestingly, the findings differ from the suggestion that higher-level undergraduate and graduate students find Chatbots useful in facilitating literature searching and summarizing readings (Berg, 2023). Interestingly, Segbenya et al.(2023) also posit that graduate students use ChatGPT to find meaning to concepts to understand and contribute to class discussions. Chan and Hu (2023) suggested that higher academic-level students also find utility in these Chatbots, such as ChatGPT, for search and academic writing and that students want feedback to improve writing skills beyond grammar-checking and brainstorming.

There were significant differences in scores among the academic levels for BI. The senior undergraduate students had the highest mean score and significantly differed from graduate students and junior undergraduate students, who had the lowest score, and the findings seem to support a strong correlation between BI and UB.

The senior undergraduate students had the highest mean score on SLO and significantly differed from graduate and junior undergraduate students, who had the lowest score. A plausible reason is that the academic study stage could influence how students perceive and utilize ChatGPT. The senior undergraduates may have more research needs and find ChatGPT valuable for tasks like literature reviews or data analysis. Even though some graduate students may be more comfortable using other traditional research tools, they can still rely on ChatGPT for literature reviews or data analysis, as discussed earlier.

Males had the highest mean scores for UB, BI, and SLO, significantly different from those of females, who had the lower scores. This finding aligns with Liang and Lee (2017) and Stöhr et al. (2024), who found that women were less enthusiastic about using AI Chatbots in higher education settings. Our findings support Stein et al. (2024) assertion that some women typically hold more negative attitudes toward AI technology than men, which may, among other causes, be explained by societal barriers that limit women's access to (and interest in) technology-based domains.

Also, both Bearman et al. (2023) and Stöhr et al. (2024) suggest that some women tend to be conservative in using AI technology and more sensitive to social influence, impacting their intention to use new technology. Women might also be more cautious about adopting new AI technological tools, especially if they have ethical concerns and their use is not mandatory, as Venkatesh and Davis (2000) suggested.

Regarding UB and BI among the age groups, the 23–27 group had the highest mean score, significantly different from that of the 18–22 group with the lowest score. This finding differed from that of Stein et al. (2024), who suggest that higher age tend to have more aversive cognitions, feelings, and behavioral intentions toward AI. We surmise that respondents from the 18–28 age group fall roughly within the millennial generation, often called "digital natives," and have grown up surrounded by technology and are comfortable integrating it into various aspects of their lives, including education.

However, this 23-27 age group might be in a crucial stage of academic development, such as being in higher-level undergraduate or graduate classes that require seeking resources and tools to improve their learning efficiency and research skills. ChatGPT could be perceived as valuable for tasks like literature reviews, data analysis, or generating innovative ideas in physics courses.

Due to a current trend in online synchronous and asynchronous innovative learning methods in STEM-higher education, where some of this group's members find themselves, they may be open to a deeper exploration of ChatGPT's utility to enhance their learning experience. They may also be curious about ChatGPT's interactive nature and self-paced user experience, which are suitable for adult learners. Finally, this age group may be nearing graduation or entering the workforce. They could be looking to develop skills relevant to the job market, where data analysis and familiarity with AI tools are increasingly sought after. Knowledge and skill in using ChatGPT in industry applications could be a way to gain a competitive edge.

5.5. Limitations

A limitation of this study is the potential for social desirability bias in surveys, where respondents may respond to enhance their institutions' image. Some students may double-major in physics and other programs, which could influence their responses if their learning outcomes require using ChatGPT for scholarly activities. Access to free campus-wide internet and ChatGPT applications was not uniform across the various universities, potentially affecting perceptions of usefulness. The response rate of 27% and the convenience of selecting specific universities could affect the generalizability of the findings. The study's findings may not be generalized beyond the respondents but add valuable insight to the current discourse on AI use in higher education. Political threats to restrict AI technologies in some countries and conspiracy theories related to the dangers of AI can adversely influence respondents' perceptions of ChatGPT use.

5.6. Conclusion: implications for theory and practice and future direction

Despite these limitations, the study confirms the robustness of the TAM in predicting ChatGPT use across different cultural and institutional contexts. The significant explanatory power of the TAM underscores its utility in understanding cross-national ChatGPT use in collegiate physics education. Perceived ease of use and social norms emerged as critical determinants of behavioral intention and user behavior, while perceived usefulness played a less direct role. This finding suggests that the simplicity and accessibility of AI tools, along with social influences, are crucial for their adoption in academic settings.

Ethical use considerations significantly influenced user behavior, highlighting the importance of addressing ethical concerns to foster responsible ChatGPT use. The negative mediation effect of ethical use on the relationship between behavioral intention and user behavior indicates that more significant ethical concerns about ChatGPT can reduce actual usage. An emphasis on clear ethical guidelines and frameworks is vital.

Demographic analyses revealed significant differences in ChatGPT perceptions and use across age groups, gender, institutions, and academic levels. Senior undergraduates exhibited higher user behavior, potentially due to greater academic demands and exposure. Males reported higher ChatGPT usage and behavioral intention scores than females, suggesting gender-specific differences in ChatGPT acceptance. Cross-cultural comparisons showed that institutional factors, such as support policies and technological infrastructure, play crucial roles in shaping ChatGPT acceptance.

From a policy perspective, we suggest tailored strategies to promote the adoption of AI Chatbots such as ChatGPT among different student groups and educational settings. Higher educational policymakers should consider demographic and cultural factors when integrating AI tools like ChatGPT into curricula to maximize their benefits and address potential ethical concerns.

Further exploration of the relationship between PU and BI as ChatGPT evolves is warranted. Examining discipline-specific factors, such as the alignment of other AI Chatbots with physics learning objectives, the role of training, and institutional policies moderating the adoption process, may be helpful. A longitudinal study on consistent AI Chatbots use, institutional support, student motivation, and learning outcomes can also be explored.

CRediT authorship contribution statement

Benjamin Agyare: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Joseph Asare:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Amani Kraishan:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Isaac Nkrumah:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Daniel Kwasi Adjekum:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Grammarly® to check spelling, language framing, and style to improve readability and ensure brevity. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Appendix A. Supplementary data

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