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Adoption of generative AI in higher education: Understanding usage through a technology acceptance model

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ABSTRACT

The aim of this study is to examine the adoption of Generative AI (GenAI) tools among faculty in higher education using a revised Unified Theory of Acceptance and Use of Technology (UTAUT) model. A quantitative survey was conducted with 244 faculty members from eight Saudi universities, and the data were analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS. The results show that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI) significantly influence the adoption of GenAI tools. Among these, PE and EE had the strongest positive impact on BI, stressing the importance of user-friendly design and faculty training, while SI had a weaker but still meaningful effect. Gender and academic position were also found to moderate adoption behaviors, indicating differences across faculty groups. This study extends the UTAUT model by introducing new moderating factors and provides empirical evidence from Saudi Arabia. It further recommends intuitive system design, technical support, training, and the development of an AI-friendly academic culture to promote effective integration of GenAI in higher education.

1. Introduction

Artificial Intelligence (AI) refers to the development of computer systems or technologies that can carry out tasks requiring human-like intelligence (Peñalvo and Ingelmo, 2023). These tasks include problem-solving, decision-making, natural language processing, image recognition, and machine learning. Generative AI (GenAI) is a subset of AI that focuses on creating new, original content based on patterns learned from existing data (Law, 2024). In contrast to traditional AI, which often analyzes or predicts based on data, GenAI produces creative outputs such as text, images, music, or even video in response to complex and varied prompts. Examples of GenAI technologies include Generative Pre-trained Transformers (GPT) for text generation and DALL-E (image generation) (Peñalvo and Ingelmo, 2023; Law, 2024). These models generate content that is both human-like and contextually relevant by utilizing sophisticated algorithms, especially neural networks such as Generative Adversarial Networks (GANs) and Transformer models (Peñalvo and Ingelmo, 2023).

The application of GenAI in higher education has increased dramatically in recent years, where it has been considered as a revolutionary tool for enhancing teaching, learning, and research (Nikolopoulou, 2024). Key applications of GenAI in education include personalized learning experiences, AI-driven virtual teaching assistants, automated content generation, and intelligent assessment tools (Wang et al., 2024). GenAI-powered personalized learning adapts educational content to individual student needs, enhancing engagement and effectiveness (Chan and Hu, 2023). Virtual teaching assistants provide instant support to students by answering questions and delivering guidance, improving accessibility and responsiveness. Additionally, GenAI automates content creation for lectures, assignments, and study materials, reducing faculty workload while ensuring dynamic and adaptive educational content. Automated assessment tools powered by GenAI streamline grading and feedback processes, enabling educators to focus more on teaching and mentorship. Mizumoto and Eguchi (2023) examined the reliability and accuracy of GenAI tools, analyzing

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over 12,000 essays scored using the GPT-3 text-davinci-003 model. Their findings indicate that GenAI enhances efficiency in essay scoring, reducing grading time while improving accuracy. Furthermore, GenAI contributes to skill development by creating immersive learning environments, such as simulations, interactive storytelling, and AI-generated educational content (Law, 2024; Nikolopoulou, 2024). By integrating GenAI, educational institutions can foster a more efficient, inclusive, and personalized learning ecosystem that meets the demands of modern education (Chan and Hu, 2023; Peñalvo and Ingelmo, 2023).

Universities are increasingly encouraged to incorporate AI technologies to enhance faculty capabilities and improve educational outcomes (Alotaibi and Alshehri, 2023; Al Fraidan, 2024). However, despite the transformative potential of GenAI, its adoption among academic staff remains underexplored (Baig and Yadegaridehkordi, 2025).

While existing research has explored technology adoption in education, there is limited empirical evidence on the specific adoption patterns of GenAI tools among university faculty. Most prior studies focus on general AI applications or learning management systems (LMSs) rather than the unique characteristics of GenAI in instructional settings. A study by Michel-Villarreal et al. (2023) highlighted the need for empirical research on user experiences with GenAI in higher education to better understand both student and faculty perceptions. Unlike conventional educational technologies, GenAI tools require faculty members to develop new digital literacy skills, navigate ethical concerns, and assess the pedagogical impact of AI-generated content (Alotaibi and Alshehri, 2023; Chan and Hu, 2023). Additionally, institutional policies and faculty perceptions regarding the reliability, accuracy, and academic integrity of GenAI-generated materials play a crucial role in shaping adoption behaviors (Wang et al., 2024). However, little attention has been given to how faculty members perceive and integrate GenAI into their teaching practices or the barriers they face in doing so. This study investigates the key factors influencing the adoption and use of GenAI tools among academic staff in Saudi universities. To achieve this, the research adapts the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) to assess the integration of GenAI in teaching. By examining the roles of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI), the study provides empirical evidence on GenAI adoption in higher education.

By addressing the factors shaping faculty adoption, this research contributes to both theoretical and practical discussions on GenAI integration in higher education. The insights gained can help universities, educators, and policymakers develop strategies to facilitate AI adoption, enhance faculty readiness, and maximize the pedagogical benefits of GenAI in higher education.

The following sections of this paper review the UTAUT framework and discuss the theoretical foundation of the study. The methodology section outlines the research design and data analysis approach, followed by a presentation and discussion of the findings. The paper concludes with final thoughts and recommendations for future research.

2. Literature review

Investigating user perceptions of GenAI tools across different contexts is crucial for their successful acceptance and integration. Several recent studies have focused on the use of AI tools in various environments, particularly the workplace and educational settings. Research has highlighted that GenAI tools can have a significant impact on user satisfaction, productivity, and overall perceptions. For example, Miyazaki et al. (2024), explored how the use of AI tools in the workplace shaped employees' perceptions of ChatGPT's effectiveness and satisfaction levels. The study, which surveyed over 300 participants aged 20 to 40, found that AI tools positively impacted productivity and performance, with older users demonstrating higher satisfaction levels. This increased satisfaction may be attributed to their greater life experience, which enabled them to recognize the value of AI tools. However, the study primarily focused on office workers, leaving out educators in higher education, a crucial demographic in understanding AI adoption within academic settings.

Another study investigated the adoption of generative AI-based tools in higher education and the level of awareness and overall sentiment towards adoption, especially the factors influencing attitudes towards large language models (LLMs). The survey was conducted with faculty members across various schools within Utah State University. The study found that users of AI tools were aware of their value and had a positive attitude toward using AI tools in LLMs. Quality enhancement and ease of use were identified as the most effective factors in the adoption of AI tools. However, faculty members expressed concerns about losing creativity with the use of AI tools. The limitation of the study is that the sample was drawn from a single university, so the results cannot be generalized to other institutions due to potential variations.

Through in-depth qualitative approaches, detailed observations, and interactions, Michel-Villarreal et al. (2023) conducted a study aimed at comprehending the wider cultural, social, and practical implications of ChatGPT within educational settings. The study explored the cultural and social factors impacting engagement with intelligent AI systems in academic contexts and recommended an empirical investigation into the most effective methods and approaches for using generative AI in education. Lau and Guo (2023) provided a comprehensive overview of the current state of AI code generation tools in computer science colleges, as well as an understanding of the perceptions of computing faculty regarding these AI coding tools. Surprisingly, the findings revealed that faculty perceptions were divided into two groups. One group encouraged the use of AI coding tools to prepare students for future jobs, while the other group advocated for policies and regulations to ban these tools.

2.1. The unified theory for acceptance and use of technology (UTAUT)

Venkatesh et al. (2003) developed the UTAUT model in 2003. The authors conducted a comprehensive literature review of technology acceptance models and analyzed them to build the UTAUT framework. The framework explains the reasons behind users adopting an information system and how they utilize it over time. UTAUT is an integration of eight different models; these models were widely used in the adoption of modern technologies. Ajzen and Fishbein's (1970) study introduced the Theory of Reasoned Action (TRA), which consists of two dimensions to understand the factors influencing individual behavior in engaging with an event; these two dimensions are the individual's attitude towards the behavior and subjective norms. In 1991, the TRA was expanded to include additional factors influencing individual intention; these factors are attitude, subjective norms, and perceived behavioral control, which collectively impact individual behavior. This expanded theory is known as the Theory of Planned Behavior (TPB) (Ajzen, 1991). Another model is the Technology Acceptance Model (TAM), which was developed by Davis (1989) to consider individual behavior toward technology, focusing on perceived usefulness (PU), perceived ease of use (PEOU), attitude, and intention to use (Davis, 1989). The Model of Personal Computer Utilization (MPCU) was introduced by Thompson et al. (1991), who adapted an existing behavioral model to predict individual computer usage (Thompson et al., 1991). The MPCU considers factors such as attitudes, social norms, habits, and anticipated outcomes to estimate how individuals use individual computers. A year later, Davis et al. (1992) introduced the Motivational Model (MM) (Davis et al., 1992). The model considers both intrinsic and extrinsic motivations as key factors influencing technology usage, highlighting the significance of perceived benefits and the enjoyment of using computers. To provide a more thorough understanding of technology adoption, the Combined Technology Acceptance Model and Theory of Planned Behavior (C-TAM-TPB) integrates the predictors of TPB with perceived usefulness from TAM (Taylor and Todd, 1995). Rogers's (1995) study investigated the factors influencing the spread of technology within social systems by introducing the Innovation Diffusion Theory (IDT). IDT includes five core constructs that focus on different areas: the innovation-decision process, the characteristics of the innovation, and the characteristics of adopters. Another perspective on computer usage is the Social Cognitive Theory (SCT), which examines how computer self-efficacy, outcome expectations, emotions, and anxiety affect computer use. This theory emphasizes the connection between self-efficacy, emotions, and the utilization of computers (Compeau et al., 1999).

UTAUT model identifies four primary factors: PE, EE, SI, and FC. These factors predict both the intention to use and the actual usage behavior of new technology. The model also considers variables such as gender, age, prior experience, and voluntariness (Venkatesh et al., 2003).

With the increasing use of technology in recent decades, researchers have focused on understanding technology adoption. The UTAUT model has been widely used in research to understand user behavior and the adoption of modern technology. The decision to adopt UTAUT over other models reviewed above is based on several considerations. UTAUT integrates and extends elements from eight major technology adoption frameworks, resulting in a more comprehensive model that captures the key determinants of user acceptance. Notably, UTAUT explains up to 70% of the variance in behavioral intention to use technology (Venkatesh et al., 2003), whereas many alternative models consider fewer factors and account for less variance. Furthermore, UTAUT’s inclusion of moderating variables provides a better understanding of how different user characteristics influence technology adoption. Given this broader scope and strong empirical support, UTAUT offers a robust theoretical foundation for investigating faculty members’ acceptance and use of technology in academic settings.

2.2. UTAUT model and generative AI tools in higher education

The UTAUT model has been widely recognized as an effective framework for evaluating technology adoption among higher education students and faculty. Numerous studies have applied this model to examine the intention to use technology in learning. For instance, research has identified key factors influencing students' acceptance of e-learning media (Abbad, 2021). Another study explored the determinants affecting students' behavioral intentions to adopt MOOCs (Massive Open Online Courses) (Chaveesuk et al., 2022). Additionally, investigations have been conducted on the acceptance and use of ChatGPT among university students across six institutions in Poland and Egypt (Strzelecki and ElArabawy, 2024). A related study integrated UTAUT with SCT to offer theoretical insights into students' adoption of ChatGPT in educational settings, particularly regarding academic integrity (Bouteraa et al., 2024). Furthermore, the UTAUT model has been applied to analyze students' intentions and actual usage of Moodle, an e-learning platform at a public university in Jordan (Abbad, 2021).

In contrast, some studies focus on faculty members' behavior regarding technology adoption.

For example, a study by Ahmad et al. (2023) examined the receptiveness of faculty members at Jordanian universities toward using digital learning tools in research, utilizing the UTAUT model. The findings indicated a high level of acceptance of digital tools among faculty members. Furthermore, Perez (2024) utilized the original UTAUT model to examine faculty members' technology adoption behavior at Marinduque State College in the Philippines, providing valuable insights into their usage patterns. The study further highlighted the positive impact of AI adoption, particularly in influencing faculty members' behavioral intentions to integrate AI tools into teaching and assignment strategies. Zaim et al. (2024) examined the integration of generative AI in English as a Foreign Language (EFL) teacher preparation within Indonesian higher education, highlighting its potential to enhance teaching efficiency and content personalization. Using the UTAUT and Activity Theory, the research analyzed factors influencing lecturers' adoption of generative AI. The results revealed that performance expectancy and social influence positively affected behavioral intention, while effort expectancy had no significant impact. Surprisingly, facilitating conditions negatively influenced intention, possibly due to lecturers' satisfaction with current resources.

The original UTAUT model includes four moderate variables: gender, age, experience, and voluntariness of use. However, in UTAUT2, voluntariness of use was removed, leaving only the remaining three. Prior research utilizing UTAUT2 has often incorporated only a subset of these moderators while also exploring additional influencing factors (Chaveesuk et al., 2022; Strzelecki and ElArabawy, 2024; Zheng et al., 2024). The UTAUT2 model has been extensively validated in empirical studies on educational technology adoption. For example, Khlaif et al. (2024) examined the adoption of generative AI in teaching and found that performance expectancy, effort expectancy, social influence, and hedonic motivation significantly influenced educators' behavioral intentions and actual usage. The study also investigated how teaching experience moderated these relationships, providing deeper insights into how familiarity with technology affects its adoption. Similarly, Cabero-Almenara et al. (2024) conducted a study involving 425 university educators to assess their perspectives on integrating generative AI into education using the UTAUT2 model. Their findings confirmed that performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation positively impacted educators' intention to adopt and engage with AI in teaching.

Given this perspective, we excluded experience as a moderating variable, as generative AI tools have not been available long enough for this factor to be significantly relevant. Instead, we replaced age with academic positions to better align with our study's focus on faculty members in higher education. However, gender was retained as a moderating variable. While most studies focus on students' acceptance and use of AI tools in educational contexts, such as ChatGPT and MOOCs, there is a significant research gap regarding how faculty members, especially in Saudi Arabia, adopt and integrate these technologies. Despite their pivotal role in the education system, limited research has explored their perceptions, challenges, and support needs for effectively incorporating AI into teaching. To address this gap, we adopted the UTAUT model to examine faculty members' behavioral intentions and adoption of generative AI tools in Saudi Arabian higher education.

3. The proposed model

Integrating GenAI into complex environments can be challenging, particularly for university faculty. Therefore, understanding their perspectives and BI toward its adoption in teaching is essential. To achieve this, several hypotheses related to the UTAUT constructs are first developed based on existing research in the field.

Venkatesh et al. (2003) defined PE as the extent to which an individual believes that utilizing a system will enhance job performance. Performance expectancy is a crucial factor in the adoption of generative AI by faculty members in higher education. If educators believe that using GenAI will enhance their teaching efficiency, improve content creation, streamline assessments, and support research, they are more likely to integrate it into their work. The ability of GenAI to generate lesson plans, provide personalized feedback, and automate administrative tasks can significantly boost faculty productivity. However, if educators perceive that GenAI does not offer substantial improvements or introduces challenges such as inaccuracies, ethical concerns, or increased workload in verifying AI-generated content, their willingness to adopt it may decrease (Alotaibi and Alshehri, 2023; Michel-Villarreal et al., 2023). Previous studies have shown that individuals' performance expectancy regarding GenAI tools significantly influences their behavioral intentions to use them (Camilleri, 2024; Khlaif et al., 2024; Zaim et al., 2024; Kim et al., 2025). This suggests that academic staff anticipate that GenAI will improve their teaching by offering innovative tools for content creation, lesson planning, student assessment, and customized learning. Faculty members believe that GenAI can enhance accuracy and elevate the quality of their work—whether in terms of creativity or insight—potentially shaping their intention to adopt it. Based on the above, the following hypotheses have been developed:

H1: PE significantly influences the user's behavioral intention to use GenAI tools.
H1a: Gender significantly moderates the relationship between PE and BI.
H1b: Academic position significantly moderates the relationship between PE and BI.

EE is defined by Venkatesh et al. (2003) as "the degree of ease associated with the use of the system." Researchers in information systems argue that people are more inclined to adopt technologies that are straightforward, understandable, and require minimal effort to use (Thompson et al., 1991; Venkatesh et al., 2003). In the context of higher education, effort expectancy is a key factor influencing faculty members' willingness to adopt generative AI tools. If educators perceive these tools as intuitive, easy to integrate into their workflows, and requiring minimal effort to learn, they are more likely to incorporate them into teaching and assessment practices (Michel-Villarreal et al., 2023). However, if GenAI tools are seen as complex or time-consuming to master, adoption may be hindered, even if the potential benefits are recognized. Several studies propose that the perceived ease of using GenAI technologies increases the likelihood of future adoption. For instance, research by Camilleri (2024) and Habibi et al. (2024) have confirmed the significant influence of effort expectancy on the intention to use ChatGPT. Similarly, a study conducted in Egypt (Ragheb et al., 2022) identified EE as a key factor affecting BI to use chatbots in education. Khlaif et al. (2024) discovered that effort expectancy influenced educators' intentions to integrate GenAI tools into their teaching. Similarly, Tran et al. (2021) applied the UTAUT model to study medical students' behavioral intention toward an AI-driven diagnosis support system, revealing a positive correlation between behavioral intention and effort expectancy. To confirm the findings of previous studies on the role of EE on BI, the current research has proposed the following hypotheses:

H2: EE significantly influences the user's behavioral intention to use GenAI tools.
H2a: Gender significantly moderates the relationship between EE and BI.
H2b: Academic position significantly moderates the relationship between EE and BI.

Venkatesh et al. (2003) described SI to the extent to which individuals feel pressured by society to adopt a particular technology. When the use of a new system or technology is mandated, people may comply out of necessity rather than personal choice (Venkatesh et al., 2003). For faculty members in higher education, social influence can play a crucial role in the adoption of generative AI (Kim et al., 2025). Academic environments often emphasize collaboration, peer influence, and institutional expectations, making faculty members more likely to adopt new technologies if they perceive that colleagues, administrators, or influential figures in their field support their use. If department heads, university leadership, or esteemed peers endorse generative AI as a valuable tool for enhancing teaching and research, faculty may feel a stronger motivation to integrate it into their work. Conversely, if there is skepticism or resistance within their academic circles, adoption may be slower. Therefore, fostering a positive perception of generative AI through institutional support, success stories, and peer advocacy could significantly impact its acceptance and usage among educators. Khlaif et al. (2024) conducted a study to examine the factors affecting faculty adoption of generative AI tools for student assessment in higher education. The findings indicate that social influence significantly impacts educators' behavioral intentions and their actual use of GenAI tools in evaluating student performance. A study by Zaim et al. (2024) examining the incorporation of generative AI in EFL teacher preparation within Indonesian higher education found that social influence had a significant positive impact on behavioral intention. This suggests that lecturers' willingness to adopt generative AI is shaped by the opinions of their peers and the broader academic community. In a similar vein, a study exploring faculty members' intention to adopt AI tools for teaching in higher education and another investigating perceptions and intentions to use ChatGPT (Camilleri, 2024) both found a strong positive correlation between social influence and behavioral intention. A recent study in Egypt (Mohamed Eldakar et al., 2025) explored the factors influencing academics' adoption or intent to adopt GenAI technologies in their research practices. The findings revealed that social influence significantly impacts perceptions of ease of use, usefulness, and intention to use GenAI tools. Hence, this study hypothesizes:

H3: SI significantly influences the user's behavioral intention to use GenAI tools.
H3a: Gender significantly moderates the relationship between SI and BI.
H3b: Academic position significantly moderates the relationship between SI and BI.

FC refers to the extent to which an individual perceives that the necessary organizational and technical infrastructure is in place to support the adoption of new technology (Venkatesh et al., 2003). Facilitating Conditions play a crucial role in the successful adoption of GenAI by faculty members in higher education. If educators perceive that their institution provides adequate technical infrastructure, training, and support, they are more likely to integrate GenAI into their teaching and research (Ahmad et al., 2023). Access to reliable internet, AI-compatible software, institutional policies, and IT support can enhance confidence in using these tools effectively. Conversely, a lack of institutional support, unclear guidelines, or insufficient training may create barriers to adoption. A study conducted by Baig and Yadegaridehkordi (2025) examining the factors affecting academic staff satisfaction and continuous use of GenAI in higher education found a positive link between facilitating conditions and the intention to use GenAI. Adequate support and resources enhance users' confidence and proficiency, ultimately increasing their willingness to continue using these tools. Al-Riyami et al. (2023) examined faculty members' acceptance of fourth industrial revolution technologies in higher education. The study revealed that facilitating conditions have a significant influence on faculty members' behavioral intention to adopt these technologies in their teaching practices. Ahmad et al. (2023) discovered that facilitating conditions have a positive impact on faculty members' intention to adopt digital learning in education, as well as their actual usage behavior. Thus, the following hypothesis is proposed:

H4: FC significantly influence user behavior in using GenAI tools and are moderated by gender and academic position.

BI represents an individual's intention or willingness to adopt a technology, whereas Use Behavior (UB) reflects its actual implementation (Venkatesh et al., 2003). The connection between these two constructs is a fundamental concept in technology acceptance research, demonstrating a well-established progression from intention to actual usage. In the context of GenAI adoption by faculty members in higher education, the relationship between BI and UB is crucial. While many educators may express a strong intention to use GenAI due to its potential benefits—such as enhancing teaching efficiency, automating assessments, and personalizing learning, this does not always translate into actual usage. Several factors, including institutional support, ease of use, and workload constraints, can influence whether faculty members follow through on their intention to integrate GenAI into their teaching and research. In their study, Zaim et al. (2024) found a strong positive correlation between lecturers' behavioral intention and their actual use behavior, emphasizing the crucial role of intention in driving the adoption of GenAI tools for teaching.

H5: BI significantly influences user behavior in using GenAI tools.

Drawing on previous studies and the proposed hypotheses, the structural model is constructed and illustrated in Fig. 1. The proposed model modifies the original UTAUT framework by adjusting its moderating variables. While the original UTAUT model includes four moderators: gender, age, experience, and voluntariness of use, the current study retains gender and introduces academic position, while excluding the remaining three. Gender was retained in line with the original model (Venkatesh et al., 2003) due to its continued relevance in educational technology research, particularly in the Saudi context. In many Saudi universities, including those represented in this study, male and female faculty often operate in separate departments with distinct administrative structures and access to training and technological resources. Empirical studies in the Gulf region further support the influence of gender on attitudes toward technological adoption, including AI (Al-Fraihat et al., 2020).

Therefore, including gender as a moderator enhances the model's cultural relevance and explanatory power.

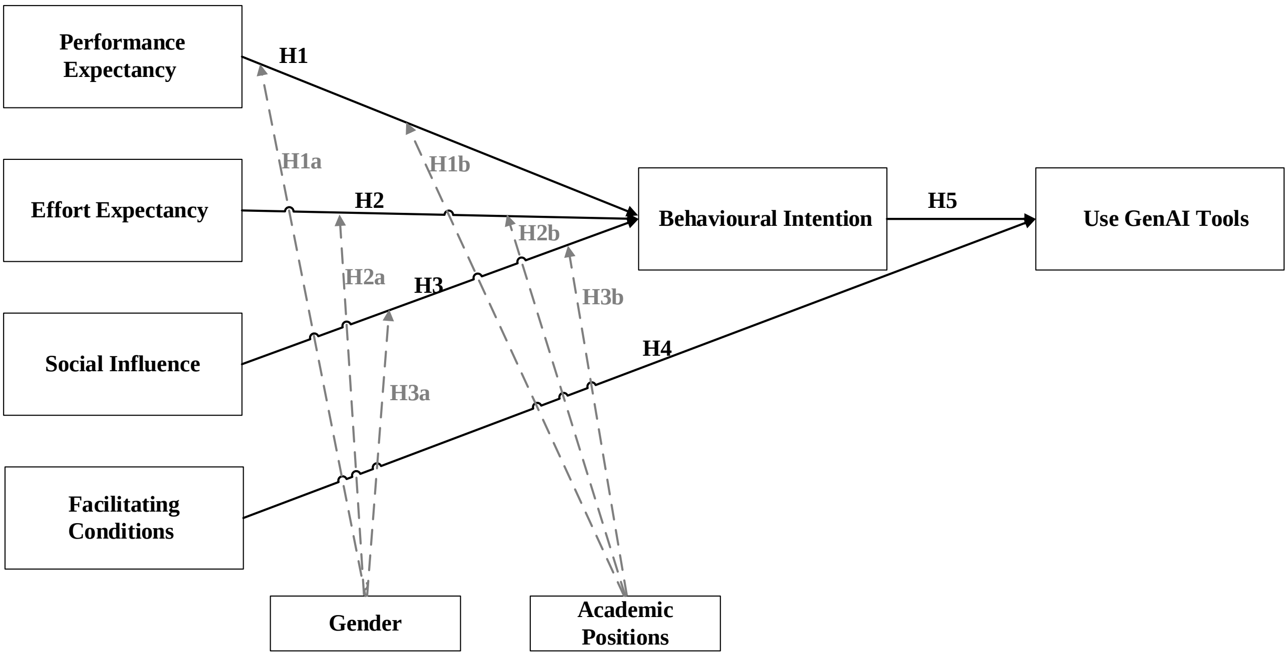

Fig. 1: Proposed model based on the UTAUT model

Age and experience were excluded because, in faculty environments, chronological age is not necessarily reflective of differences in technology adoption behavior. Faculty members of similar ages may occupy different academic roles, each with varying degrees of autonomy, responsibility, and exposure to innovation. In place of these constructions, academic position was introduced as a more appropriate moderator. In the Saudi higher education system, academic rank (e.g., lecturer, assistant professor, associate professor, full professor) significantly influences access to resources, expectations for innovation, decision-making authority, and professional development opportunities. It is important to note that there is a lack of sufficient prior research specifically examining academic position as a moderating factor in technology adoption among faculty. Most existing studies focus on demographic variables such as age and gender, without considering how professional seniority influences perceptions of adopting new technologies like Generative AI. This gap highlights the need for further investigation to better understand how academic hierarchy shapes attitudes toward innovation in higher education contexts.

Finally, the construction of voluntariness of use was removed because, at the time of the study, the use of Generative AI tools was voluntary and not influenced by any university mandates or policies. Since all faculty members were adopting, or choosing not to adopt, these tools at their own discretion, there was no meaningful difference in this factor across the sample. This revised model aligns with recent research showing that traditional moderators may not fully capture the adoption behavior.

4. Research design and methodology

The proposed model was developed based on insights from previous studies. To ensure the model's relevance and applicability within the context of higher education, a questionnaire was administered as part of a quantitative research approach. This approach is well-suited for examining relationships between variables and enables the investigation of theory-driven research questions and hypotheses.

4.1. Data collection

The validity and reliability of the model were assessed through a pilot study involving 25 academic specialists with expertise in survey design from universities in Saudi Arabia. These experts were asked to provide feedback on the model variables and their relationships to ensure that the instrument was appropriate for the research context and accurately measured the intended constructs. To evaluate the variables, a five-point Likert scale ranging from "strongly disagree" to "strongly agree" was utilized. The results of the pilot study demonstrated that Cronbach's alpha and reliability coefficients exceeded 0.7, while the average variance extracted (AVE) met the 0.5 threshold. These findings confirm that all variables meet the established criteria for both validity and reliability. Table 1 outlines the six constructions along with their corresponding items.

A total of 24 items were measured to examine faculty members' acceptance of Generative AI tools in higher education. According to the Saudi law of Ethics of Research on Living Creatures, the proposed study does not require ethical review, as it does not involve individuals under the age of 15, poses no risk of physical or mental harm, collects no sensitive personal data, and is non-invasive with no use of deception.

After validating the survey, a web-based survey was distributed; to reach as many faculty members as possible, the survey centers at Saudi universities were contacted by the authors to distribute the survey invitation to academic staff across their universities. A consent form was provided to the participants before starting the survey. The survey was designed to be anonymous, and no personally identifiable information was collected. Also, participants were assured of confidentiality and the voluntary nature of their participation. Clear instructions emphasized that there were no right or wrong answers, encouraging participants to respond honestly and reflectively. All data were securely stored on password-protected devices accessible only to the research team. Participants were informed about the voluntary nature of their involvement, assured of their anonymity, and instructed to respond honestly. These measures helped. These measures helped minimize ethical risks and protect participants' privacy throughout the study.

minimize ethical risks and protect participants' privacy throughout the study. Nonetheless, the potential limitations inherent in self-reported data privacy are acknowledged and should be considered when interpreting the findings.

The sample size was determined based on guidelines from Partial Least Squares Structural Equation Modeling (PLS-SEM), which recommend selecting a sample size ranging from 5 to 10 times the number of items (indicators). In this study, the total number of items across all variables was 26, leading to an optimal sample size range of 130 to 260 participants.

Table 1: Construct definition and measurement items (Venkatesh et al., 2003)

Construct	Description	No. of items
PE	The degree to which academic staff believe that using GenAI tools will enhance their teaching effectiveness.	4
EE	The perceived ease of learning and using GenAI tools for teaching purposes.	4
SI	The extent to which colleagues and peers influence faculty members' decisions to adopt GenAI tools.	3
FC	The availability of technical support, resources, and infrastructure that enables the effective use of GenAI tools.	3
BI	Faculty members' willingness and intention to adopt GenAI tools in teaching, influenced by their attitudes and perceptions.	4
UGT	The actual implementation and engagement of faculty members in using GenAI tools for teaching.	4

The survey was conducted between August 2024 and January 2025. Prior to analysis, responses that showed uniform answers across all items were excluded from the analysis, as such patterns may indicate disengagement or inauthentic responses. A total of 244 valid responses were retained for analysis. The sample included participants with diverse academic qualifications and gender representation. Table 2 summarizes the demographic information. The sample consists of 59% females and 41% males. In terms of academic positions, the majority are mid-career faculty members, with 36.1% Assistant Professors and 27.9% Associate Professors, while Lecturers and Professors each account for 18%. Additionally, most participants (77%) have over seven years of experience, whereas 8.2% have three years or less. The intermediate group (4–7 years of experience) represents 14.8%, indicating that the sample primarily consists of seasoned professionals.

Table 2: Summary of demographic information

Item	Category	Frequency	Percentage
Gender	Male	100	41%
	Female	144	59%
Academic position	Lecturer	44	18%
	Assistant professor	88	36.1%
	Associate professor	68	27.9%
	Professor	44	18%
Years of experience	≤ 3 years	20	8.2%
	Between 4 and 7 years	36	14.8%
	More than 7 years	188	77%

To gain a clearer understanding of the range of GenAI tools used by participants, Part 1 of the survey, participants: "What generative AI tools do you use?" with the option to select multiple tools. The predefined choices included ChatGPT, Gemini, Poe, AI12, DALL·E, and Other. The responses indicated that 69.2% of participants reported using ChatGPT, followed by 20.5% who used Gemini. The usage rates for other tools, including Poe and DALL·E, ranged between 3% and 5%, reflecting relatively limited adoption compared to ChatGPT and Gemini.

4.2. Data analysis and results

To assess the model constructs, the collected data were analyzed using the PLS-SEM, performed with SmartPLS 4 software. The analysis employed the path weighting scheme algorithm with default initial weights and a maximum of 3,000 iterations. Additionally, bootstrapping was used in this analysis, a non-parametric approach that does not rely on distributional assumptions. A total of 5,000 bootstrap samples were generated to evaluate the statistical significance of the PLS-SEM results.

To examine the reliability of reflectively defined constructs, indicator loadings were analyzed. A loading exceeding 0.7 indicates that the construction explains more than 50% of the indicator's variance, thereby demonstrating a satisfactory level of item reliability.

To ensure internal consistency reliability, Cronbach's alpha was computed. The results, presented in Table 3, indicate that the model exhibits strong reliability, with values falling within the acceptable range of 0.7 to 0.9. Furthermore, the AVE values for all constructions exceed the recommended threshold of 0.5, as proposed by Hair et al. (1998). The Heterotrait-Monotrait (HTMT) ratio of correlations technique was applied to evaluate discriminant validity, as proposed by Henseler et al. (2015). A recommended threshold of 0.90 indicates potential discriminant validity concerns when construction exhibits conceptual similarity. However, for more distinct constructions, a stricter cutoff of 0.85 is advised (Henseler et al., 2015). As shown in Table 4, all computed HTMT values fall below the 0.85 threshold, indicating that discriminant validity is not a major concern.

Table 3: Construct reliability and validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
PE	0.939	0.943	0.956	0.846
EE	0.932	0.951	0.951	0.830
SI	0.702	0.884	0.827	0.635
FC	0.704	0.762	0.830	0.622
BI	0.959	0.961	0.971	0.892
UGT	0.952	0.953	0.969	0.912

Table 4: HTMT values

	BI	FCs	EE	PE	SI	UGT
BI						
FCs	0.844					
EE	0.847	0.805				
PE	0.831	0.691	0.831			
SI	0.833	0.788	0.824	0.834		
UGT	0.799	0.78	0.774	0.847	0.833	

The research hypotheses were tested by analyzing the correlations among construct variables, path coefficients (β), T-statistics, and their associated p-values. The results indicate that hypotheses H1, H2, and H5 were statistically significant at the 0.01 probability level, while H3, H4, H3a, and H1b were significant at the 0.05 probability level. However, H1a, H2a, H2b, and H3b did not achieve statistical significance at the 0.05 probability level. Consequently, the study supports hypotheses H1, H2, H3, H4, H5, H3a, and H1b, demonstrating a significant positive effect. In contrast, H1a, H2a, H2b, and H3b were not supported due to a lack of statistical significance. All results are summarized in Table 5.

The path coefficients indicate the strength of relationships within the model. PE, EE, and SI all have a positive effect on BI. Specifically, PE exerts a strong influence on BI (β = 0.687), while EE has a moderate effect (β = 0.302). Additionally, FC moderately impact the use of GenAI tools (UGT) (β = 0.248). BI has a very strong positive effect on UGT (β = 0.932).

Regarding moderating effects, gender negatively moderates the relationship between PE and BI (β = -0.052) and EE and BI (β = -0.08), while positively moderating the influence of SI on BI (β = 0.277). Similarly, academic and BI (β = 0.015) and SI and BI (β = 0.008), but negatively moderates PE and BI (β = -0.108). The coefficient of determination (R^2) measures how well the independent variables explain variance in the dependent variable and helps assess the model's predictive strength. R^2 values range from 0 to 1, where a higher R^2 indicates greater explanatory power.

According to Sarstedt (2008), R^2 is categorized as high ($R^2 > 0.5$), moderate ($R^2 > 0.3$), and weak ($R^2 > 0.1$). Additionally, Sarstedt et al. (2022) noted that R^2 values below 0.02 indicate no effect.

The results from SmartPLS are presented in Fig. 2, which illustrates the outer weights and loadings for all indicators, along with the R^2 values for BI and UGT. The key finding is that the R^2 value for BI is 0.847, indicating that 84.7% of the variance in BI is explained by the independent variables. Similarly, the R^2 value for UGT is 0.869, meaning that 86.9% of the variance in UGT can be attributed to the independent variables.

Table 5: Hypothesis testing

Hypothesis	Path coefficient (β)	Standard deviation	T-statistics	P-values	Supported
H1: PE -> BI	0.687	0.136	5.045	0.000	Yes
H2: EE -> BI	0.302	0.127	0.599	0.000	Yes
H3: SI -> BI	0.124	0.121	0.076	0.045	Yes
H4: FC -> UGT	0.248	0.104	2.373	0.043	Yes
H5: BI -> UGT	0.932	0.018	52.555	0.000	Yes
H1a: Gender x PE -> BI	-0.052	0.256	0.761	0.223	No
H2a: Gender x EE -> BI	- 0.080	0.155	0.516	0.076	No
H3a: Gender x SI -> BI	0.277	0.198	1.402	0.015	Yes
H1b: Academic position x PE -> BI	-0.108	0.089	1.866	0.038	Yes
H2b: Academic position x EE -> BI	0.015	0.079	1.483	0.739	No
H3b: Academic position x SI -> BI	0.008	0.076	0.002	0.888	No

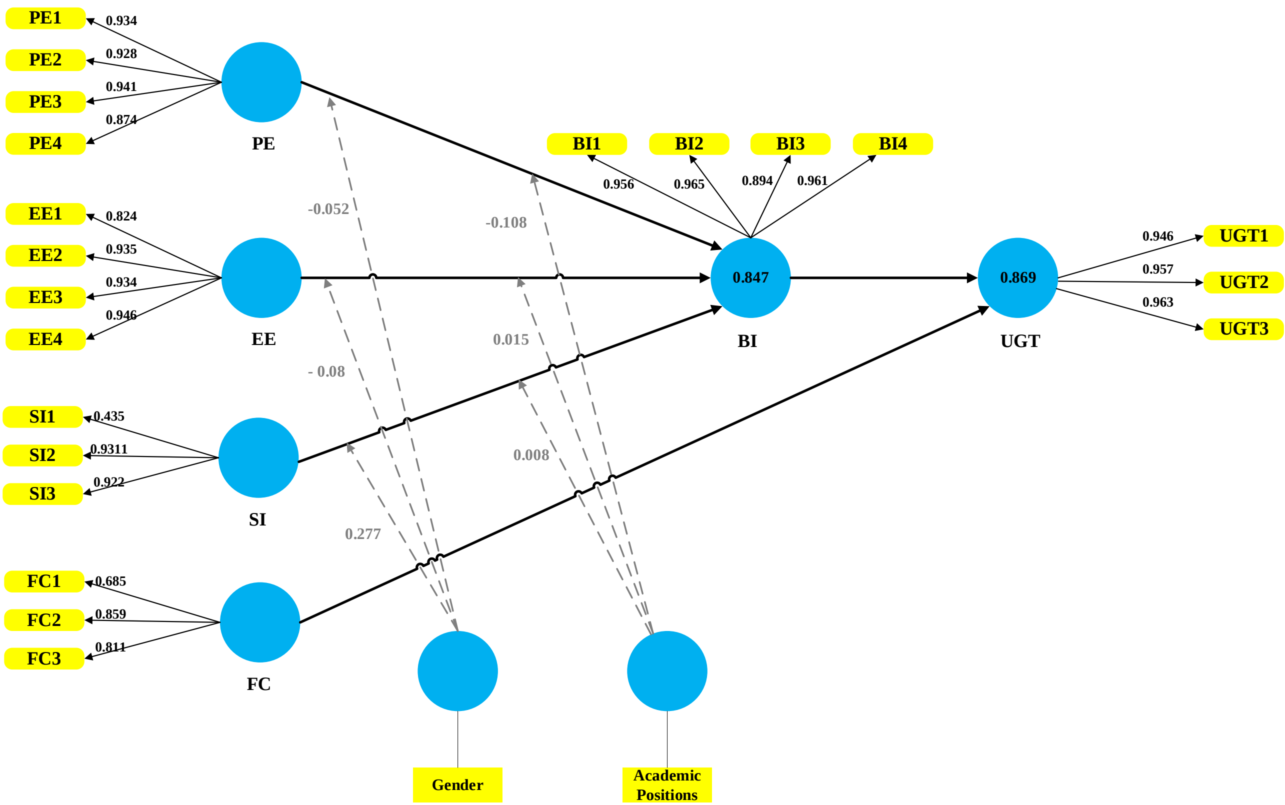

Fig. 2: Model results in SmartPLS (the outer weight and loading for all indicators, and R2) and the path coefficients for the moderating variables

5. Discussion

From the results displayed above, the study found that PE significantly influences BI, indicating that academic staff are more likely to adopt GenAI tools when they perceive them as beneficial for enhancing efficiency and productivity. This finding aligns with prior research suggesting that perceived usefulness is a key driver of technology adoption in educational settings. Moreover, it aligns with global findings demonstrating PE's significance: for example, survey data from UK faculty show over 70% anticipate increased future GenAI use once they recognize its value, a U.S. study in which 83% of 284 academics reported finding GenAI tools were beneficial to their academic work, suggesting broader adoption and increased usage ahead. The strong influence of PE on BI found in the present study is higher than the effect sizes reported in some Western contexts. This is explained by the higher education focuses on AI technologies driven by national initiatives such as Saudi Vision 2030. Investments in AI infrastructure and faculty development have created an environment that enhances faculty perceptions of GenAI's productivity benefits.

Similarly, EE was found to have a significant impact on BI, confirming that the perceived ease of use of GenAI tools influences adoption intentions. This result emphasizes the role of AI interfaces in adoption, as investigated in a previous study (Bouteraa et al., 2024).

Moreover, the study result is consistent with the broader literature on technology adoption, where ease of use is a key determinant of user acceptance in higher education settings (Dwivedi et al., 2021; Strzelecki and ElArabawy, 2024).

SI had a weaker impact on BI, suggesting that while peer and higher education institutions' encouragement can influence the adoption of GenAI tools, individual perceptions of usefulness and efficiency play a role. Questionnaire responses indicated that faculty members who use GenAI in teaching recognize its advantages and acknowledge the necessity of its integration. Similar findings have been reported in previous studies on technology adoption, where social influence was identified as a secondary but notable factor affecting behavioral intention (Bouteraa et al., 2024). The relatively weaker role of SI compared to other factors differs from findings in regions where collaborative academic cultures and peer networks strongly affect technology adoption. This difference may stem from cultural or organizational characteristics in Saudi universities, where individual motivation and autonomy appear to have a greater impact than social pressure.

The findings also confirm that FC significantly impact Use of GenAI Tools (UGT), indicating that access to resources, technical support, and infrastructure plays a critical role in enabling actual usage. Additionally, the findings indicate that faculty members expect adequate technical assistance and guidance to facilitate adoption. This is aligned with previous research emphasizing that a well-established technological environment is essential for technology adoption (Li and Zhao, 2021). FC also plays an especially important role here due to ongoing improvements in technical support and digital literacy programs tailored to new AI tools, setting this context apart from countries with more established digital infrastructures (Li and Zhao, 2021).

Finally, BI was found to have a strong positive impact on UGT. This suggests that faculty members with a high intention to use GenAI tools are significantly more likely to actively engage with them. These findings emphasize the importance of enhancing PE and EE, as both constructs strongly influence BI and, consequently, the actual use of GenAI tools. The study results indicate that many faculty members are willing to integrate GenAI into their teaching and perceive it as a modern and valuable tool. Similar findings have been reported in research examining the role of behavioral intention in technology adoption (Strzelecki and ElArabawy, 2024).

For moderating effects of gender and academic position, the analysis showed that gender significantly moderates the relationship between social influence and behavioral intention to adopt Generative AI tools. In particular, the relationship was stronger among female participants, suggesting that social norms and peer expectations may play a role in attitudes toward technology adoption in this group. This finding aligns with previous research indicating that social influence often affects technology acceptance differently across genders, potentially due to variations in professional networks or perceived social expectations.

In contrast, gender did not significantly moderate the effects of PE or EE on BI. This outcome suggests that perceptions of usefulness and ease of use are relatively consistent between male and female faculty members in this context, which is notable given that some studies in other regions have reported gender-based differences in these dimensions.

Regarding academic position, the analysis indicated a significant negative moderating effect on the relationship between PE and BI. Faculty in higher academic ranks appeared less influenced by the perceived usefulness of GenAI tools, possibly due to greater confidence in existing methods or less pressure to adopt new technologies. However, academic position did not significantly moderate the effects of effort expectancy or social influence. This may reflect attitudes across academic ranks when it comes to the perceived ease of use and the role of peer influence, confirming the relevance of these factors regardless of seniority.

5.1. Policy implications

The study's findings confirm the critical need for universities to implement targeted training programs, especially for senior faculty, to build confidence and competence in effectively using GenAI tools. Given that faculty members are more likely to adopt GenAI when they recognize its productivity benefits, system developers should emphasize these advantages, such as enhanced content generation, to encourage adoption. Since ease of use significantly influences behavioral intention, comprehensive training initiatives, including practical workshops, tutorials, and hands-on sessions, are essential for equipping faculty with the necessary skills for successful integration. Additionally, establishing a robust technical support infrastructure, such as dedicated help desks and clear user guides, helps minimize barriers and fosters sustained use. Equally important is fostering a supportive institutional environment where both formal networks (university encouragement, policies, and incentives) and informal networks (peer mentorship and recommendations) actively promote adoption. Aligning these efforts with broader national strategies like Saudi Vision 2030 can increase resources and institutional commitment, facilitating an approach to digital transformation. Finally, addressing ethical considerations related to GenAI use through comprehensive policy frameworks and faculty training is essential to ensure responsible, trustworthy adoption. Collectively, these coordinated actions will empower faculty members to fully leverage GenAI tools, thereby advancing teaching quality, research productivity, and the overall modernization of higher education in Saudi Arabia.

6. Conclusion and future directions

This study offers valuable insights into the key factors shaping the adoption and usage behavior of GenAI tools among academic staff in Saudi universities. The research framework is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), with modifications tailored to more effectively assess faculty members' adoption and integration of GenAI in teaching. A questionnaire survey was administered to academic staff across eight universities in Saudi Arabia, resulting in 244 responses. The data was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The findings highlight the significant influence of PE, EE, SI, FC, and BI on GenAI adoption. Specifically, PE and EE had strong positive effects on BI, emphasizing the need for intuitive user interfaces and comprehensive faculty training programs to facilitate adoption. In contrast, SI had a weaker impact on BI, suggesting that peer and institutional encouragement may be less influential than perceived usefulness and ease of use in driving adoption.

This study has certain limitations. Firstly, while data collection included participants from multiple universities in Saudi Arabia, the sample remains geographically limited. Future research should expand the study to a larger number of academic institutions and include international comparisons to explore how cultural and institutional differences influence GenAI adoption. Additionally, discipline-specific analyses could provide further insights into how faculty members in various academic fields perceive and integrate GenAI tools into their teaching practices. Secondly, this study relied exclusively on quantitative analysis, which may not fully capture the subjective perspectives of faculty regarding GenAI adoption. Future studies should consider a mixed-methods approach, integrating qualitative research methods such as in-depth interviews and focus groups to gain richer insights into faculty perceptions, challenges, and concerns regarding GenAI implementation. Furthermore, while this study examined the moderating effects of gender and academic position, future research could explore the impact of additional factors such as teaching experience, technological proficiency, and institutional policies on GenAI adoption. Investigating longitudinal adoption patterns would also provide a deeper understanding of how faculty attitudes and behaviors evolve over time as AI technologies continue to develop. Finally, future research could examine the pedagogical impact of GenAI tools, assessing their effectiveness in enhancing student engagement, learning outcomes, and academic performance. Evaluating potential ethical and academic integrity concerns related to GenAI-assisted teaching and assessment could also contribute to developing best practices for responsible AI integration in education.

List of abbreviations

AI	Artificial intelligence
AVE	Average variance extracted
BI	Behavioral intention
C-TAM-TPB	Combined technology acceptance model and theory of planned behavior
DALL-E	Generative AI image creation model
EFL	English as a foreign language
EE	Effort expectancy
FC	Facilitating conditions
GAN	Generative adversarial network
GenAI	Generative artificial intelligence
GPT	Generative pre-trained transformer
HTMT	Heterotrait–Monotrait ratio
IDT	Innovation diffusion theory
LLM	Large language model
LMS	Learning management system
MM	Motivational model
MOOC	Massive open online course
MPCU	Model of personal computer utilization
PE	Performance expectancy
PEOU	Perceived ease of use
PLS-SEM	Partial least squares structural equation modeling
PU	Perceived usefulness
SCT	Social cognitive theory
SI	Social influence
TAM	Technology acceptance model
TPB	Theory of planned behavior
TRA	Theory of reasoned action
UB	Use behavior
UGT	Use of GenAI tools
UTAUT	Unified theory of acceptance and use of technology
UTAUT2	Extended unified theory of acceptance and use of technology

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Compliance with ethical standards

Ethical considerations

This study complied with ethical research standards involving human participants. Informed consent was obtained from all participants before data collection. Participation was voluntary, responses were anonymous, and no personal identifying information was collected. All data were treated with strict confidentiality and used solely for academic purposes.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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