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ORIGINAL STUDY

Exploring University Students' Acceptance of Generative AI for Writing: An Extended Technology Acceptance Model (TAM 3) Perspective

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ABSTRACT

Generative AI presents significant potential for improving students' writing, and its acceptance is influenced by varied factors. The present study aims at exploring the factors by examining six vital constructs of Technology Acceptance Model (TAM) 3 (Venkatesh & Bala, 2008)—academic relevance, output quality, self-efficacy, playfulness, anxiety, and perceived enjoyment—and their impact on perceived usefulness, perceived ease of use, and behavioral intention of students. Using a quantitative research approach, a sample size of 345 university students from Computer Science, Management Science, and Arts and Humanities voluntarily participated in an online cross-sectional survey questionnaire. The data was analyzed by SPSS 23.0 and SmartPLS 4.0 for exploratory and confirmatory factor analysis. Academic relevance ($\beta = .378^{***}$) and perceived ease of use ($\beta = .456^{***}$) were identified as significant predictors of students' perceived usefulness of (Gen) AI in their writing as compared to the output quality of (Gen) AI, which was found to be an insignificant factor of perceived usefulness. The study also reveals that playfulness ($\beta = 0.332^{**}$) and perceived enjoyment ($\beta = 0.449^{***}$) were the primary factors influencing students' perceived ease of use, unlike anxiety and self-efficacy, which showed statistically insignificant effects. The findings of the study further suggest that perceived usefulness ($\beta = 0.606^{***}$) and ease of use ($\beta = 0.227^{*}$) are key enablers of the behavior of students' intention to adopt (Gen) AI in the future.

Keywords: Generative AI, TAM3, Perceived usefulness, Perceived ease of use, Behavioral intention

Introduction

The inception of the 21st century has brought a major shift in the educational landscape due to the evolution of technologies, namely Artificial Intelligence (AI) (Baidoo-Anu & Ansah, 2023). In 2016, a major breakthrough took place in the realm of computer science,

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where an AI-trained program, AlphaGo, designed by Google, defeated a chess game champion. Since then, artificial intelligence has been an important element of education. AI in language education can be understood as the employment of AI applications, which majorly includes chatbots, intelligent tutoring systems, speech recognition, translation, and now (Gen) AI. Wu et al. (2022) state that to enhance the effectiveness of AI in education, students' preparedness and the factors that influence their willingness should be investigated from a student-centered learning perspective. Thus, it is vital to investigate the factors that affect students' adoption of (Gen) AI in English language learning.

In the third decade of the 21st century, technological advancements and transformations have led to the introduction of large language models (LLM) such as ChatGPT, Bing AI, and Google Bard, which can "predict, comprehend, and generate texts in a highly accurate and human-like fashion" (Liu & Ma, 2023, p. 2). These tools have the capability of generating text with minimal user input, thus enabling the generation of quality content across various disciplines in academic writing. Such development marks a vital move from traditional AI in English language learning, which mainly served as assistive functions, including grammar checkers and automated spelling checking. On the contrary, (Gen) AI can be described as not reactive but generative in nature, having the unique ability of writing essays, summarizing huge texts, and outlining, while significantly reducing the time required for content creation (Batchu, 2024; Ullmann et al., 2024).

Such a transformation in English language learning can be marked as significant, since the writing domain of the English language has always posed serious challenges for both learners and educators. Cognitively and linguistically, writing requires a higher degree of language familiarity, such as planning, organization of ideas, varied vocabulary use, and grammatical fluency and accuracy. Chatbots can bridge such gaps by providing support in terms of brainstorming ideas, coherence, and language accuracy, offering both linguistic assistance and cognitive scaffolding during the overall writing process.

Researchers have started exploring the pedagogical implication of (Gen) AI in English writing. Previous studies show that students who interact with AI often result in enhancement of their overall language fluency. However, employment of (Gen) AI in English writing also comes with pedagogical implications. Applications such as ChatGPT, which can generate text like a human and can be used by students in their writing, thus avoiding intellectual efforts; this often results in plagiarized content and academic dishonesty (Monib et al., 2024; Plecerda, 2024). (Gen) AI can diminish higher cognitive thinking, and over-reliance can hinder learners' problem-solving skills (Chavez et al., 2024). This debate made language educators evalaute the factors responsible for effective language learning through technology (Batool et al., 2025). As a result, researchers have called for beyond-surface-level research into how students accept, adopt, and perceive these applications in their academic pursuits.

Despite a plethora of research, there remains a gap in the existing literature on how students from diverse linguistic backgrounds and low-resourced educational contexts interact with and adopt (Gen) AI in their English writing (Arshad et al., 2025; Arshad et al., 2026). Much of the existing research has its origin in advanced-technology settings, especially in the Global North, where access to technology is high and familiarity with digital tools is widespread. Such studies often compromise the challenges encountered by developing states where internet availability, professional development, and most importantly, institutional support are minimum.

Pakistan provides a particularly relevant context for examining the adoption of (Gen) AI in English language learning. English occupies a unique sociolinguistic position in the country, functioning both as the medium of instruction in higher education and as a language associated with socioeconomic mobility and professional advancement (Irshad, 2016; Rahman, 2020). Many students enter into their university education with a significant gap in academic writing proficiency (Rehman et al., 2023). Functional English and Expository Writing courses are mostly their first formal encounter. In such a context, (Gen) AI may serve as a timely and personalized support. However, without a comprehensive understanding of students' acceptance, language educators and policy makers may risk the integration that may not be consistent with learners' individual needs and preferences.

Generally, there has been a positive discourse about the use of AI; however, in academia, it has serious concerns such as academic dishonesty and plagiarism. In response, some institutions banned AI instantly, a move that is compared with the pocket calculator when it was thought to be a threat to mathematics education (Barrett & Pack, 2023; Arshad et al., 2026). Some schools have restricted the use of AI tools; however, many institutions have shown confidence that their academic integrity policy is robust enough to handle state-of-the-art technologies (Barrett & Pack, 2023). Keeping in view its relevance in English language teaching and learning, the Air University, Islamabad, Pakistan, has designed its (Gen) AI policy, which made it mandatory for English teachers to make use of such technologies in their language classroom. In addition, it permits students to have up to 15% AI-generated content in their academic writing assignments. The use of (Gen) AI in English writing is vital to ensure that students are well equipped with the right technologies to improve their English language learning. As this technology is rapidly evolving, it is essential to explore to what extent students accept it in their English writing.

The current study is vital in its scope of (Gen) AI and its implementation in the English language learning. By exploring factors that influence students' use of (Gen) AI, this study would serve as a reference for English language educators in the contentious debate over the acceptance, adoption, and rejection of (Gen) AI in English writing. The current inquiry is vital, as it is in alignment with the promotion of AI in education relevant to SDG-4, which is *Quality Education*, outlined by UNESCO to achieve sustainable development goals by 2030. The present study, thus, formulates the following research questions:

1. What factors influence students' perceived usefulness towards use in English writing?
2. What factors influence students' perceived ease of use towards use in English writing?
3. How do perceived usefulness and ease of use inform students' behavioral intentions regarding use of (Gen) AI in English writing?

Literature review

AI as precursor to (Gen) AI

The term AI was first coined and used by McCarthy in 1956 in a proposal that was part of the Dartmouth conference. In fact, AI was the central topic of the conference. That's why McCarthy is regarded as the father of AI by many, and the Dartmouth conference is seen as an important event dedicated to the theme of AI (Papaspyridis & La Greca, 2023). McCarthy defined AI as "how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves" (McCarthy et al., 2006, p. 12). In contrast, (Gen) AI is the extension of AI that consists of a Large Language Model (LLM). (Gen) AI made its impacts visible with the launch of a pioneering tool called ChatGPT in November, 2022. It utilizes "deep learning techniques to analyze and generate text" (Su & Yang, 2023, p. 357). Ali et al. (2023) asserts that the emergence of ChatGPT has the potential to impact learning objectives and activities in education. Thus, a single innovation of new technology that can sum up the beginning of the third decade of the 21st century from the lens of digital revolution and digitization would be the tool called ChatGPT.

(Gen) AI in English writing

Recent advances in artificial intelligence (AI) have transformed various aspects of education, particularly English language learning and teaching (ELT). AI has attracted considerable attention in ELT because of its potential to enhance the quality, accessibility, and personalization of language instruction (Gyawali & Mehandroo, 2022). AI-powered applications, including speech recognition, chatbots, and machine translation, have been increasingly integrated into language learning to facilitate communication and language acquisition (Thadphoothon, 2022). In educational settings, AI functions as a language tutor by providing personalized learning experiences and immediate feedback (Sumakul et al., 2022). Earlier AI applications primarily supported writing through features such as sentence autocompletion, grammar correction, and vocabulary suggestions (Alharbi, 2023). However, the emergence of (Gen) AI has significantly expanded these capabilities by enabling learners to brainstorm ideas, draft, revise, and refine academic texts more efficiently (Hsu, 2023). Moreover, (Gen) AI provides contextualized language practice and feedback that can enhance language acquisition among English language learners (Nguyen & Hoang, 2025). Despite these pedagogical benefits, researchers emphasize the importance of addressing ethical concerns, including plagiarism and responsible AI use (Yi, 2024), while highlighting that successful classroom integration depends on teachers' digital literacy and their ability to guide students in critically evaluating AI-generated content (Kim & Ahn, 2024).

Empirical studies consistently demonstrate the positive impact of AI-assisted writing tools on learners' writing performance. For example, Dizon & Gayed (2021) found that Grammarly significantly reduced writing errors among Japanese EFL learners, suggesting that AI-based writing assistants provide valuable support for novice writers. Similarly, Mizumoto & Eguchi (2023) reported that ChatGPT-based automated essay scoring produced reliable and accurate evaluations, with further improvements achieved by incorporating linguistic features. These findings indicate that AI can effectively support both writing development and assessment by providing timely feedback and enhancing evaluation accuracy.

Recent scholarship has also highlighted the broader pedagogical value of (Gen) AI. Jabeen (2023) described ChatGPT as suitable "for general use for fun and as a literature writing assistant" (p. 33), noting that its interactive interface facilitates brainstorming, feedback, and idea refinement, thereby promoting creativity and innovation (Cranfield et al., 2023; Imran & Almusharraf, 2023, as cited in Jabeen, 2023). Nevertheless, the author cautioned that the quality of AI-generated output depends on users' prompts and that ChatGPT "lacks the human intuition and creativity that underpin truly inspired storytelling" (Chen et al., 2023, as cited in Jabeen, 2023). Likewise, Afzaal et al. (2020) emphasized AI's role in facilitating context-sensitive language learning and personalized meaning-making, while Imran & Almusharraf (2025) argued that the successful adoption of educational innovations depends on sound pedagogical practices that foster meaningful learning. Similarly, Bashir et al. (2025) demonstrated that technology-enhanced multimodal pedagogy significantly improves learners' motivation and willingness to communicate in English, further reinforcing the educational value of AI-supported learning environments.

Collectively, these studies establish the pedagogical potential of AI and (Gen) AI in improving writing, language learning, learner engagement, and assessment. However, the existing literature has predominantly focused on instructional applications and learning outcomes, with limited attention to the psychological and technological factors that influence students' acceptance and continued use of (Gen) AI for academic writing. Consequently, empirical research grounded in the Technology Acceptance Model (TAM 3) is

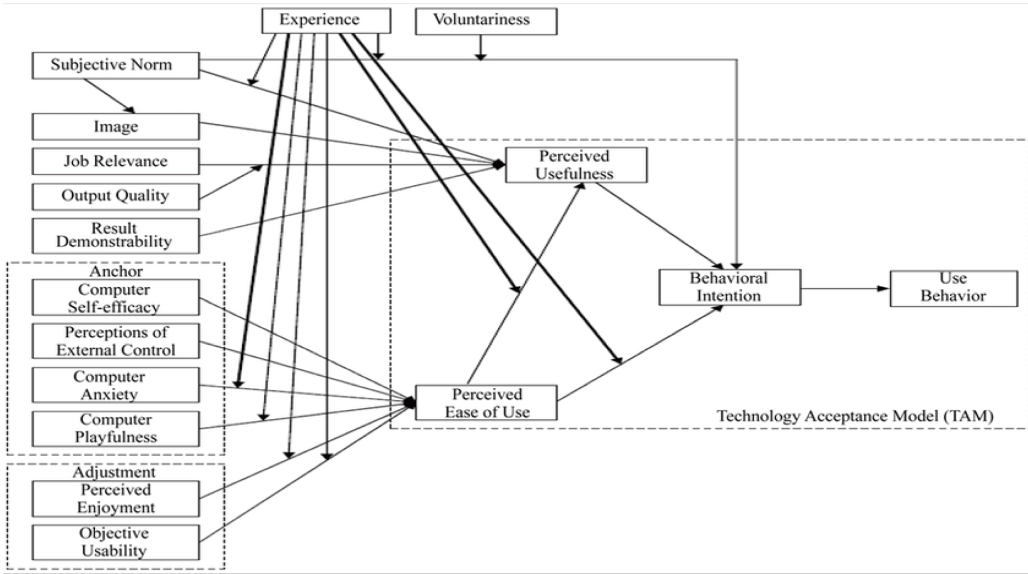

Fig. 1. Technology Acceptance Model 3.
[Source: Venkatesh & Bala, 2008]

needed to examine how factors such as academic relevance, output quality, self-efficacy, playfulness, anxiety, and perceived enjoyment shape students' perceived usefulness, perceived ease of use, and behavioral intention to adopt (Gen) AI for academic writing. The TAM3 framework used in the current study , as proposed by Venkatesh & Bala (2008), is depicted in Fig. 1.

Technology Acceptance Model 3

A number of models are available to gauge the acceptance of information systems, namely the Theory of Planned Behavior, Theory of Diffusion of Innovation, Unified Theory of Acceptance and Use of Technology (UTAUT), TPACK, and TAM. It has been acknowledged that TAM explains users' adoption, denial, and use of technology in various fields, including educational technology and computer-assisted language learning (CALL) (Liu & Ma, 2023). In prior models, TAM is most widely used and incorporated in research, as it is a well-established model to identify various cognitive and psychological factors that influence individual willingness, adoption, intention, and acceptance of different technologies. Two of the primary and fundamental determinants of TAM are perceived usefulness (PU) and perceived ease of use (PEU), which have direct or indirect impacts on behavioral intention (BI). One's behavioral intention (BI) about any technology is influenced by these two elements, which entails that a technology would be accepted by its potential user if it were both convenient and useful (Choi et al., 2022). TAM is not a suitable model for organizations such as libraries, which are based on rules, but is vital in the exploration of individual acceptance of technology (Ajibade, 2018).

In English language learning, TAM is also employed to understand students' perceptions of technology use. Several studies have been conducted on how students perceive technology use such as e-learning (Mizher & Alwreikat, 2023), virtual learning environments (Faiqoh & Ashadi, 2023), and MOOCs (Meet et al., 2022). TAM is basically a business and technology model. However, its integration in English writing is also important. In the English language, it is vital that students use technology effectively and creatively. Thus, in the present study, TAM is a suitable model to explore factors that influence students' acceptance and use of (Gen) AI in English writing.

Hypotheses and model development

The current study aims to look at the factors that influence students' acceptance of (Gen) AI in their English language writing. By utilizing the TAM model, it would assist in understanding how TAM constructs are connected in understanding students' acceptance of (Gen) AI in their writing. Moreover, the current research takes three core constructs of perceived usefulness, perceived ease of use, and behavioral intention along with six external factors such as academic relevance, output quality, self-efficacy, playfulness, anxiety, and perceived enjoyment, aiming to investigate the influence of these constructs on each other and core elements of the TAM model. Fig. 2 presents a modified version of the Technology Acceptance Model 3 (TAM3) based on the framework proposed by Venkatesh & Bala (2008).

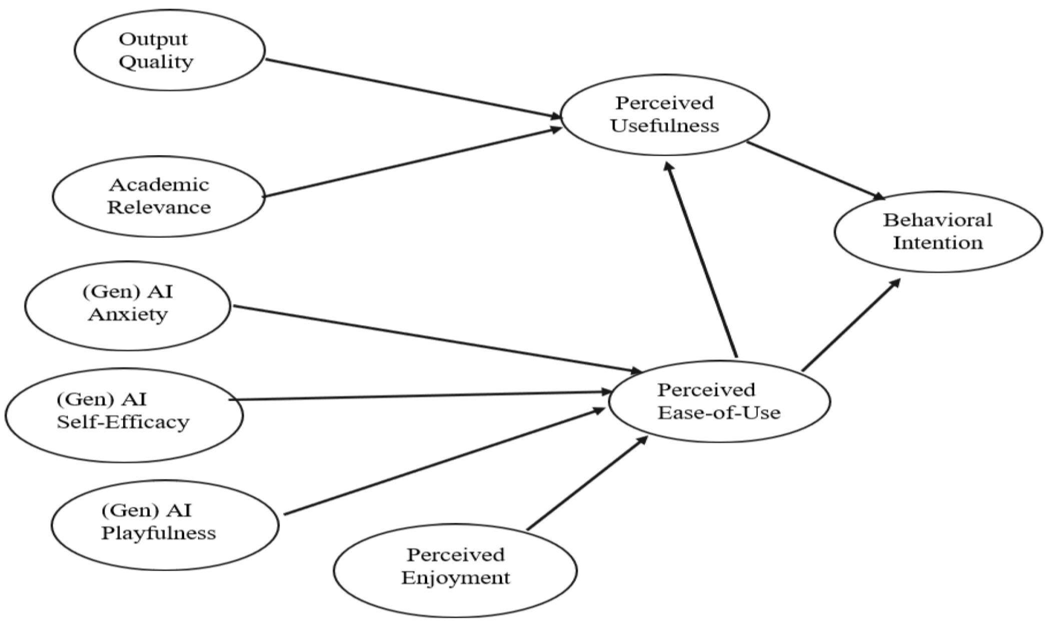

Fig. 2. Modified model for this study.

Perceived usefulness

Perceived usefulness (PU) refers to the degree to which an individual believes that utilizing a specific system (Gen AI) will improve his/her respective job performance (Adenuga et al., 2019). Many studies have investigated the significant and positive relationship between PU and behavioral intention (Zhang et al., 2023; Abdullah et al., 2016; Akmal, 2017). In the present study, PU can be understood as the degree to which English students perceive that the use of (Gen) AI will enhance their English writing performance and productivity. Thus, the present study suggests the following hypothesis:

H1: Perceived usefulness of (Gen) AI in English language studies positively influences students' behavioral intention.

Perceived ease of use

Perceived ease of use (PEOU) means the degree or extent to which an individual thinks that using a specific system would require no effort (Liu & Ma, 2023). Users are more likely to embrace technologies that are intuitive and require minimal effort to operate. Studies indicate that ChatGPT's user-friendly interface and ease of use contribute to its acceptance among students (Kanont et al., 2024; Ghimire & Edwards, 2024). However, one study interestingly found that as (Gen) AI tools become more intuitive, learners may perceive them as less helpful, challenging traditional assumptions of the Technology Acceptance Model (TAM) (Kanont et al., 2024). Different studies have explored the positive impact of PEOU on BI in various contexts; for instance, Al-Adwan et al. (2023) explored the substantial influence of PEOU in university students' adoption of metaverse-based learning platforms. In the present study, PEOU can be understood as the degree to which students perceive that the use of (Gen) AI in English writing will require no mental effort. Thus, the study proposes following hypotheses:

H2: Perceived ease of (Gen) AI use of positively influences students' behavioral intenstion.

H3: Perceived ease of (Gen) AI positively influences students perceived usefulness.

Behavioral intention

Behavioral intention (BI) an important construct that influences students' acceptance of technology. Behavioral intention means students' usage of (Gen) AI in their English writing in the future. Their intention depends on perceived usefulness and ease of use, which are the primary predictors of future technology use. Effort expectancy, which is perceived ease of use in TAM, has a positive impact on behavioral intention if used in association with performance expectancy (perceived usefulness in TAM) (Zhu et al., 2023).

Academic relevance

Venkatesh & Bala (2008) define job relevance as "an individual's perception regarding the degree to which the target system applies to his or her job" (p. 277). The basis for the choice of academic relevance in the current research is based on the underlying theoretical argument that reinforces the cognitive process of job relevance and compatibility, which holds that users make perceived usefulness judgments by making comparisons to the extent a new technology can function per their expectation (Saroia & Gao, 2018). This impact is supported by several studies that show the significant influence of job relevance on learners' perceived usefulness while accepting distinguished technologies in language learning; for instance, Alharbi & Drew (2014) explored this relationship in the context of mobile learning management systems, while Zhang et al. (2023) identified a significant yet positive relation of AI acceptance in education. Thus, academic relevance (AR) is used in the present study context. In the current study, job relevance can be understood as English students' perception regarding the degree to which (Gen) AI is applicable and relevant to their English writing. Thus, the following hypothesis is proposed:

H4: Academic relevance of (Gen) AI positively influences English students' perceived usefulness.

Output quality

TAM elements, such as job relevance and output quality, significantly affect the acceptance of technology and influence perceived usefulness (Ramazani, 2013). Output quality (OQ), in the context of (Gen) AI, refers to the accurate, coherent, and valuable response generated by the applications such as ChatGPT (Shahzad et al., 2024). High-quality output is vital, as it influences students' perceived usefulness of a technology. When students perceive that AI generates a well-organized and appropriate response to a given prompt, they are more likely to perceive it as a useful tool, thus resulting in their intention to use it. Several studies have confirmed the positive relation between output quality and perceived usefulness. Previous literature has identified output quality as a positive influence over PU; for instance, Papakostas et al. (2023) explored the positive association with perceived usefulness in the context of mobile augmented reality adoption in education by using the extended TAM model. Chaka (2023) explored the accuracy and output quality of three applications and compared their responses in selected areas of applied Linguistics studies. Zobeidi et al. (2023) explored the positive correlation in the online learning context during the Covid-19 pandemic. This study proposes:

H5: Output quality of (Gen) AI positively influences English students' perceived usefulness.

(Gen) AI Self-efficacy

(Gen) AI Self-efficacy (GASE) is an important predictor of learners' learning, and their success is dependent on self-efficacy while using different technologies (Qashou, 2021). Jin (2014) found that as compared to generic computer self-efficacy, application-specific (e.g. Generative AI) is a more powerful predictor of perceived ease of use (PEOU). Several studies have confirmed that self-efficacy has a positive impact on PEOU. Kilic (2014) investigated the significant influence of computer self-efficacy over PEOU in the Moodle context; however, Thongsri et al. (2020) identified computer self-efficacy influence on PEOU in the e-learning context. Similarly, Zhang et al. (2023) investigated a similar relation among pre-service teachers' acceptance of AI in education. Jin (2014) explored the positive relation in e-book acceptance among college students. Self-efficacy, in the context of (Gen) AI, means the extent to which an individual believes that he or she has the potential to carry out particular tasks related to English language learning using (Gen) AI. The present study proposes:

H6: (Gen) AI self-efficacy positively influences students' perceived ease of use.

(Gen) AI Anxiety

(Gen) AI Anxiety (GAA) is defined as a person's extent of discomfort that they encounter while considering using technology (Algerafi et al., 2023). Anxieties associated with AI are also termed "technophobia," and three factors play a vital role in its enhancement: confusion between human and computer tools, the absence of humans from AI-performed tasks, and the inadequacy in how technological evolution is perceived (Ayanwale et al., 2022). AI anxiety differs from computer anxiety, as AI makes independent decisions and operates automatically, which can create unexpected results for the users. Previous studies identified the negative influence of anxiety on PEOU; for instance, Zhang et al. (2023) explored pre-service teachers' acceptance of AI. Similarly, Abdullah et al. (2016) identified no increasingly significant association between anxiety and PEOU in the context of e-learning. The study conducted by Islamoglu et al. (2021) has explored no influence of anxiety on PEOU in the context of pre-service teachers' adoption of mobile technology. Anxiety, in the current domain, refers to the degree of an individual's apprehension or fear when he/she encounters the likelihood of using (Gen) AI for English writing activities. The present study proposes following hypothesis:

H7: (Gen) AI anxiety negatively influences students' perceived ease of use.

(Gen) AI Playfulness

(Gen) AI Playfulness (GAIP) refers to a person's "tendency to interact spontaneously, inventively, and imaginatively" with technology/computers (Padilla Meléndez et al., 2013). However, Abdullah et al. (2023) define Playfulness as the extent of "enjoyment, joyfulness, and pleasure" in utilizing technological tools to gain new knowledge. Yang et al. (2021) argues that the interpretation of the research model can be enhanced if perceived playfulness is viewed as an inherent motivation to be included in the TAM. Salloum (2018) stated that the individual's playfulness is essential when the system acceptance is in the initial phases. Since (Gen) AI is in its infancy stage and yet to be explored by studies, it's vital to take into consideration the playfulness construct, which can enhance the explanatory power of the TAM model. Faqih & Jaradat (2015) identified a positive relationship between playfulness and PEOU in investigating mobile commerce technology acceptance. In the context of social media usage for educational purposes, Salloum et al. (2021) found playfulness a major predictor of perceived ease of use, highlighting the significant role of enjoyment in improving the usefulness of a technology. Thus, following hypothesis is proposed:

H8: (Gen) AI playfulness positively influences students' perceived ease of use

Perceived enjoyment

Perceived enjoyment (PE) refers to the extent to which using a certain technology/system is perceived and considered enjoyable in itself, apart from any negative impact on performance that can result from system use (Venkatesh & Bala, 2008). PE is an important factor that explains adoption and rejection. When the student understands that utilizing a system (e.g., Gen AI) is enjoyable, there is a greater probability that s/he will have a significant influence on the ease of use of such a system (Salloum, 2018). The positive association between PE and PEOU has been consistently identified in the previous literature in different technologies. For example, Tao et al., 2022) identified the prior relation in the context of online MOOCs (Massive Open Online Courses); however, Abdullah et al. (2016) investigated the most widely used factors that influence students' e-learning by employing an extended model of TAM. Olajide (2023) adopted the UTUAT technology model and investigated the positive relation between perceived enjoyment and perceived ease of use in the execution of mobile learning. In the present study, perceived enjoyment is when the use of (Gen) AI in English writing is perceived as a pleasurable activity in itself, independent of any potential consequences that may be expected. In this study, the researcher proposes:

H9: Perceived enjoyment of (Gen) AI positively influences students' perceived ease of use.

Methodology

Research design

The present research can be located in the positivist paradigm. Guba and Lincoln (1994) define a paradigm as a" world view" guiding a researcher's investigation. The current study has used a quantitative cross-sectional survey design. Paltridge & Phakiti (2015) define cross-sectional research as a research in which researchers gather data from one or more individuals or a group within a brief period (e.g., utilizing questionnaires and interviews). In technology acceptance and adoption studies, questionnaire surveys are considered appropriate tools for determining the relationships between various constructs included in the study model (Qashou, 2020).

Context of the study

The research was conducted at the Air University, Islamabad, Pakistan. The targeted participants were undergraduate students of BS [English, Psychology, Computer Science, Information Technology, Business Studies, Accounting & Finance, and Aviation Management] enrolled in Semester 1 of Fall 2023 and Semester 2 of Spring 2024. The present study took into account the Functional English and Expository Writing subjects, as these subjects are taught in earlier BS semesters.

Sampling technique

To increase the efficiency and validity of the research, purposive sampling was employed. The purposive sampling technique is also called “judgmental sampling,” where the subject is selected according to predetermined criteria (Putra & Samopa, 2018). Before the data collection procedure, the approximate sample size was computed by using *the N:q* rule proposed by Kline (2023) for SEM (Structural Equation Modelling) analysis. *N: q* represents the recommended sample-to-parameter ratio, such as 20:1 (Cai et al., 2023). In the current study, the researcher took nine variables and their impact on each other. The recommended sample size for present research was 180 for nine variables. However, the study collected 345 participants’ responses, which are approximately twice the required number of survey questionnaire responses.

Research ethics

In the present study, the research ethics approval form was filled out by the researchers in order to carry out the research. After its approval from the English Department of Air University, we formally proceeded with the research. In addition, the participant’s information sheet was also filled out by the researchers and shared with the instructors of all the intended classes, followed by the participants’ consent regarding their participation in the present study before their actual participation. The consent form was also inserted in the questionnaire. Students were also made aware of the confidentiality of the data, and it was emphasized that their provided data would be only utilized for research purposes. This was done to ensure that participants’ privacy is not compromised, and honest and transparent responses are encouraged.

Data collection procedure

The present study was conducted in three different phases, which are visible in Fig. 3. The first phase dealt with the development of a survey questionnaire followed by a pilot study before proceeding to actual research. In the second phase of the study, a questionnaire was administered to get students’ perspectives on (Gen) AI acceptance in English language learning. The third phase was focused on the analysis and interpretation of the collected data. The collected data was statistically analyzed through SPSS 23.0 and SmartPLS version 4.0. Descriptive statistics (i.e., mean and standard deviation) were calculated for the yielded data by using SPSS. However, SEM analysis was carried out by SmartPLS. As the present study is based on SEM (structural equation modeling), it consists of measurement and structural models. On one hand, the measurement model includes item loading, Cronbach’s alpha, composite reliability, average variance, and confirmatory factor analysis. On the other hand, the structural model consists of path coefficient and multiple regression, etc., which are used for hypothesis testing. Here, it is pertinent to mention that all the statistical tools of the measurement model must have standardized

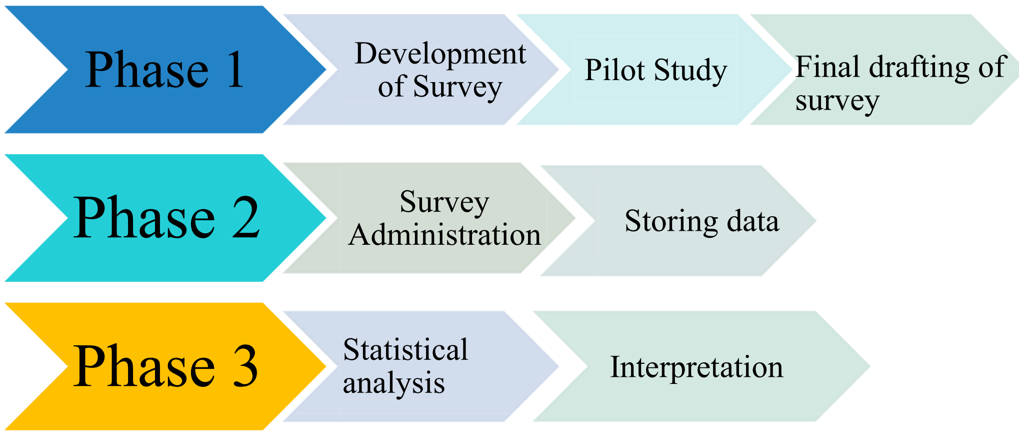

Fig. 3. Phases of the study.
[Source: Irshad, 2016]

values before proceeding to the structural model. The structural model works only if the measurement model has achieved the appropriate values of statistical items.

Phase one of the study

Embarking on formal procedures of the research incepted with the notion of development of the survey. The questionnaire aimed at acquiring responses from students regarding the use of (Gen) AI and its acceptance in English writing. The preceding assumption led the researchers to design an appropriate survey that can be used as a research instrument. Acceptance was based on usefulness, ease of use, and students' behavioral intention to utilize it in the future or not.

Survey instrument

An online questionnaire was developed to gauge students' perspectives from previous studies on their acceptance of (Gen) AI in English language learning based on steps as

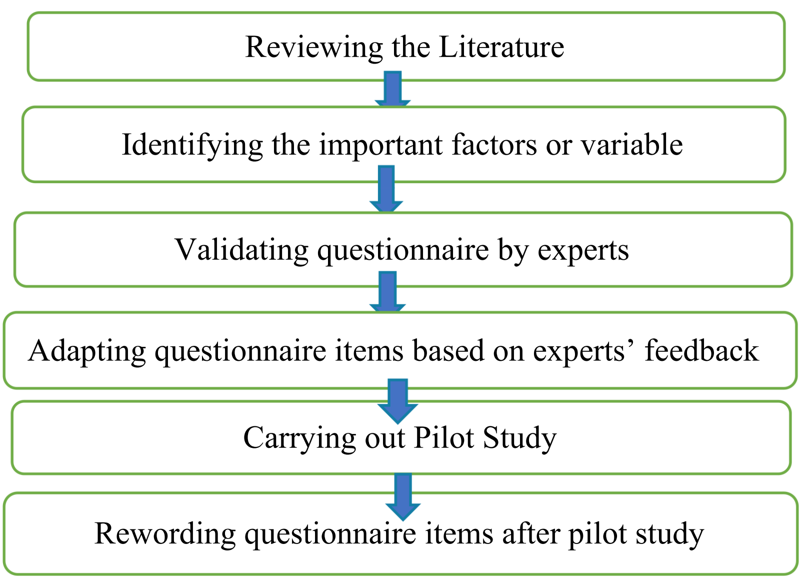

Fig. 4. Stages of development of the questionnaire.
[Source: Izkair & Lakulu, 2023]

depicted in Fig. 4. An adapted questionnaire from previous studies was prepared (Abdel & Al-Yuzbaki, 2023; Huang et al., 2021; Nadlifatin et al., 2020; Salloum et al., 2019; Mohammadi, 2015), in accordance with the objectives of our study. This took place at the end of the course. The content of the questionnaire was validated by one foreigner and local professor who has expertise in technology integration in language learning and teaching. Further, three different pilot studies were conducted for the reliability of the questionnaire items.

A Likert scale was incorporated, which represents different levels of acceptance of each concept or construct. The survey consisted of 35 items to understand the students' perspectives about acceptance. Each of the questionnaire items is related to a particular construct. The constructs were academic relevance (4 items), output quality (4 items), self-efficacy (4 items), anxiety (4 items), Gen AI playfulness (4 items), perceived enjoyment (3 items), perceived ease of use (4 items), and perceived usefulness (4 items). Students gave their opinions based on a 5-point Likert scale from 1 to 5, where 1 indicated strongly disagree, 2 agree, 3 neutral, 4 agree, and 5 strongly disagree.

Pilot studies

For the main study to be successful, the research at hand first underwent several pilot studies. The pilot study is vital, as it involves screening vague statements that do not align with the desired objectives. Table 1 provides an overview of the pilot studies. One of the prominent features of the second pilot study was that all questionnaire items were modified. For the third pilot study, the number of participants was increased.

Table 1. Pilot study results.

No.	Date	Level	No. of participants	Items with low reliability
Pilot study 1	25th Dec, 2023	BS Psychology & English students	29	PU1, PU2, AR1, AR3, AR4, GAP2, GAP3, GAP4, GASE1, GAA2, GAA3, PE1, PEOU2, PEOU4
Pilot study 2	1st Apr, 2024	MPhil Linguistics students	22	AR1, AR2, AR3, PEU2, OQ3, GAIP1, GAIP2, GAIP3
Pilot study 3	3rd Jun, 2024	BS English and Psychology	71	AR4

Phase two of the study

The participants were approached through electronic means such as Email and WhatsApp. The internet-based questionnaire survey was leveraged due to its wide accessibility, as it provides high-quality responses. Through all modes of the questionnaire filling, participants were provided the survey questionnaire links. We visited every individual class for the data collection. The researchers, at first, approached the class teacher of BS English first semester to collect data for a pilot study. After showing her research ethics and participant's information form, the teacher allowed us to explain our research objectives to the participants. We shared the questionnaire link with the class teacher on the WhatsApp application, which in return was shared by the teacher with the students. The data collected from Google form was uploaded into SPSS 23.0 and SmartPLS 4.0 for further analysis.

Phase three: Analysis

Descriptive statistics

Before the start of analysis, a normality test was conducted using SPSS 23.0 as visible in Table 2. All the measured items had skewness and kurtosis within the appropriate range.

Table 2. Descriptive statistics.

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Academic Relevance	345	3.2483	.66474	–.553	.144	.068	.287
Output Quality	345	3.3260	.69278	–.499	.144	.774	.287
Self-Efficacy	345	3.4441	.76151	–.455	.144	.194	.287
Anxiety	345	3.1215	.79905	–.173	.144	–.341	.287
Playfulness	345	3.2185	.71871	–.571	.144	.840	.287
Perceived Enjoyment	345	3.3054	.79029	–.741	.144	.538	.287
Perceived Usefulness	345	3.5119	.69711	–.563	.144	1.134	.287
Perceived Ease of Use	345	3.5533	.69962	–.774	.144	1.316	.287
Behavioral Intention	345	3.4353	.78288	–.586	.144	.717	.287
Valid N (listwise)	345						

Most variables in the data indicated negative skewness ranging from -.774 to -.173. This indicates that most items in the data were skewed to the left side. All values of kurtosis and skewness are below the range of |1| and |2|, suggesting that all items' values in the data were near to normal distribution (An et al., 2023). All the constructs have mean values between 3.12 and 3.55, indicating a generally positive perception of these factors in the present study. SD values range from 0.66 for AR to 0.80 for GAA. Lower SD suggests less variability in responses for academic relevance, while higher SD for AI anxiety shows more varied opinions.

Confirmatory factory analysis (CFA)

Confirmatory Factor Analysis (CFA) involves the validity of variables in the measurement and structural models. Confirmatory Factor Analysis (CFA) is a statistical technique primarily used to test the collected data, whether it fits or not with the prior model structure. SmartPLS version 4.1.0.9 is used in the present study. CFA involves testing a hypothesized model with given factors and evaluating how well the model fits the observed data. The assessment of the outer model, which is also called the measurement model, consisted of four measurements: 1) outer loading, 2) reliability test (including both Cronbach's alpha and composite reliability), 3) convergent validity, and 4) discriminant validity (Cai et al., 2023).

Cronbach's alpha (α) & composite reliability

Table 6 shows item loading, which ranges from .770 to 93.8, clearly exceeds the criteria of .708 for item loading, and is suggested as they show that more than 50% of the variance is explained by the respective construct, thus achieving satisfactory item reliability (Hair et al., 2018). The next step is checking the construct reliability, which refers to the internal consistency of items in the construct and measures the specific construct. Generally, higher values mean that constructs are more reliable. Internal consistency was validated by using two measures: Cronbach's alpha (α) and composite reliability (CR). In the reliability test of scale, the internal Cronbach's α values were computed, where all items and constructs have values above .70 (An et al., 2023). Hair et al. (2018) recommends the following values of composite reliability: Reliability values above 0.60 and less than 0.70 are considered "acceptable"; values that lie between 0.70 and 0.90 are declared as "satisfactory to good"; values higher than 0.95 are troubling as they indicate items in a construct are repeated, thus reducing the validity of the construct. Reliability values of the constructs are between .704 and .924, which suggests that all constructs have achieved acceptable reliability values. Composite reliability is one of the important measures in SEM, as it evaluates the internal consistency of a set of items measuring a construct. It's considered valuable when Cronbach's alpha, a traditional measure of reliability, may not be suitable due to certain limitations. Composite reliability is calculated from CFA (confirmatory factor analysis), which provides a more appropriate measure of construct reliability, especially in models that are not simple (Haji-Othman & Yusuff, 2022; Widhiarso, 2016).

Convergent and discriminant validity

The convergent validity of the scale was established by using average variance extracted (AVE). Average extracted variance means the similarity between different items of a variable (Yilmaz et al., 2023). As visible from Table 6, the AVE values ranged from .627 to .814. These computed values significantly exceed the recommended requirement of .50, thus indicating the establishment of convergent validity, which is important in the measurement model before moving to the structural model.

Discriminant validity is used for construct distinction to ensure that all constructs measure different concepts. In the present study, three tests of discriminant validity were used: 1) the heterotrait-monotrait ratio (HTMT), 2) the Fornell-Larcker criteria, and 3) cross-loading. In order to validate the result, the researchers first employed the Fornell-Larcker criteria of discriminant validity as outlined in Table 3. The Fornell-Larcker criterion means when the square root of AVE (average variance extracted) for each construct is more than the correlation of the same construct between the same concept or any other construct (Cai et al., 2023). However, this measurement of discriminant validity received criticism, as research shows that in the context of the VB (variance-based) method in SEM, it may minimize factor loading and maximize relations in the structural model (Deng & Yu, 2023). As a result, to further verify the discriminant validity, the researchers moved to conduct the HTMT ratio of correlation, which is considered robust in SEM analysis.

Table 3. Fornell-Larcker criterion.

	AR	BI	GAA	GAIP	GAISE	OQ	PE	PEU	PU
AR	**0.792**								
BI	0.567	**0.902**							
GAA	0.317	0.344	**0.880**						
GAIP	0.576	0.569	0.141	**0.817**					
GAISE	0.398	0.417	0.289	0.430	**1.000**				
OQ	0.540	0.441	0.258	0.404	0.354	**0.829**			
PE	0.550	0.669	0.264	0.588	0.459	0.422	**0.879**		
PEU	0.440	0.612	0.180	0.569	0.286	0.460	0.620	**0.835**	
PU	0.594	0.750	0.237	0.602	0.458	0.444	0.697	0.636	**0.816**

The second test conducted for the discriminant validity was HTMT. HTMT refers to the average of correlations between items of the same construct (Cai et al., 2023). The HTMT ratio is widely recommended in the context of SEM analysis, as it provides straightforward measurement and assessment of the results (Dirgiatmo, 2023). The HTMT correlation result, as illustrated in Table 4, indicates all variables have values below the criteria of $<$ .85 as recommended by Hair et al. (2019). Since all constructs have an HTMT value under .85 which indicates that all constructs were significantly distinct and were not excessively correlated, discriminant validity was achieved.

The final test for discriminant validity was cross-loading. Cross-loading means the item loading of every component belonging to that specific construct should have a higher value than any other construct (Deng & Yu, 2023). Overlooking cross-loadings can lead to inappropriate conclusions about the different relationships within constructs, thus

Table 4. Heterotrait-metrotrait ratio (HTMT) correlation.

	AR	BI	GAA	GAIP	GAISE	OQ	PE	PEU	PU
AR									
BI	**0.690**								
GAA	0.400	**0.383**							
GAIP	0.792	0.680	**0.187**						
GAISE	0.465	0.438	0.302	**0.511**					
OQ	0.728	0.506	0.310	0.565	**0.421**				
PE	0.711	0.751	0.301	0.753	0.494	**0.507**			
PEU	0.565	0.712	0.219	0.716	0.315	0.578	**0.753**		
PU	0.761	0.848	0.271	0.772	0.503	0.533	0.817	**0.782**	

Table 5. Cross-loading.

	AR	BI	GAA	GAIP	GAISE	OQ	PE	PEU	PU
AR1	**0.789**	0.471	0.300	0.533	0.397	0.499	0.493	0.326	0.460
AR2	**0.697**	0.321	0.189	0.388	0.383	0.374	0.438	0.217	0.372
AR5	**0.777**	0.525	0.232	0.445	0.339	0.531	0.382	0.419	0.518
BI1	0.589	**0.884**	0.278	0.628	0.373	0.438	0.566	0.444	0.628
BI2	0.541	**0.889**	0.310	0.481	0.422	0.479	0.574	0.584	0.728
BI3	0.547	**0.938**	0.296	0.535	0.435	0.470	0.591	0.509	0.657
BI4	0.465	**0.898**	0.345	0.621	0.441	0.512	0.679	0.588	0.668
GAA1	0.159	0.265	**0.845**	0.089	–0.203	0.278	0.190	0.133	0.109
GAA2	0.300	0.344	**0.910**	0.186	–0.234	0.311	0.272	0.131	0.243
GAA3	0.318	0.293	**0.878**	0.197	0.210	0.174	0.225	0.100	0.206
GAIP1	0.516	0.477	0.042	**0.854**	0.240	0.368	0.509	0.511	0.463
GAIP2	0.622	0.539	0.171	**0.817**	0.266	0.327	0.466	0.485	0.523
GAIP4	0.433	0.361	0.111	**0.701**	0.307	0.387	0.493	0.328	0.439
GAISE1	0.321	0.292	0.070	0.178	**0.840**	0.403	0.288	0.406	0.319
OQ1	0.438	0.446	0.263	0.357	0.386	**0.843**	0.409	0.448	0.450
OQ2	0.469	0.312	0.244	0.326	0.387	**0.780**	0.293	0.276	0.315
OQ3	0.422	0.314	0.152	0.377	0.347	**0.727**	0.330	0.439	0.314
PE1	0.452	0.622	0.264	0.522	0.426	0.483	**0.878**	0.523	0.581
PE2	0.525	0.523	0.140	0.631	0.351	0.363	**0.833**	0.471	0.556
PE3	0.574	0.615	0.268	0.619	0.481	0.417	**0.923**	0.575	0.681
PEU1	0.259	0.466	0.190	0.386	0.364	0.465	0.454	**0.780**	0.562
PEU3	0.426	0.538	0.078	0.503	0.311	0.421	0.581	**0.889**	0.540
PEU4	0.488	0.526	0.186	0.557	0.404	0.524	0.512	**0.807**	0.565
PU1	0.559	0.623	0.132	0.591	0.347	0.402	0.663	0.523	**0.836**
PU2	0.464	0.589	0.175	0.540	0.371	0.332	0.567	0.460	**0.804**
PU3	0.504	0.557	0.148	0.554	0.311	0.392	0.418	0.425	**0.802**
PU5	0.514	0.667	0.273	0.432	0.559	0.468	0.607	0.540	**0.791**

influencing model fit measures in confirmatory factor analysis (CFA) (Cao & Liang, 2023). Literature shows that researchers must be careful when examining the results, as ignoring cross-loadings can compromise the validity of findings as well as the generalizability of the results (Loftin, 1991). As illustrated in Table 5, all items have high values of factor loading in their respective constructs and across other constructs. Hence, discriminant validity was established.

Structural (Inner) model

After meeting all the criteria by the measurement model, the researcher advanced to evaluate the structural model, emphasizing on the overall interaction among nine constructs. The structural model analysis consisted of a range of specified criteria, including

Table 6. Measurement model results.

Items	Factor loading	VIF	Cronbach α	CR (rho_c)	AVE
AR1	.850	1.739	0.704	0.834	0.627
AR2	.753	1.534			
AR5	.770	1.246			
OQ1	.875	1.680	0.776	0.868	0.688
OQ2	.852	1.886			
OQ3	.755	1.448			
GASE3	1	1	n/a	n/a	n/a
GAA1	.80	1.627	0.853	0.911	0.775
GAA2	.926	3.060			
GAA3	.904	2.929			
GAP1	.896	1.997	0.750	0.856	0.668
GAP2	.865	1.792			
PE1	.879	2.236	0.852	0.910	0.772
PE2	.830	1.850			
PE3	.925	2.750			
PU1	.843	2.020	0.833	0.888	0.666
PU2	.826	1.949			
PU3	.799	1.779			
PU5	.795	1.611			
PEU1	.779	1.564	0.783	0.874	0.698
PEU3	.886	2.097			
PEU4	.838	1.638			
BI1	.885	3.127	0.924	0.946	0.814
BI2	.889	2.673			
BI3	.938	4.890			
BI4	.897	3.103			

carrying out a collinearity test by using VIF, assessment of the coefficient of determination (R2), evaluation of the path coefficient values (β), and identifying the predictive relevance (Q^2). All these criteria are used in the present study by utilizing the PLS-method. In addition, all these criteria are outlined by Ma (2024). However, Benitez et al. (2020) included the model fit in the assessment of the structural model.

Multicollinearity VIF

The VIF (variance inflation factor) is considered an important parameter in the realm of the Technology Acceptance Model (TAM) for evaluating multicollinearity among various independent variables. VIF aids in the identification of correlation among different independent variables in TAM. A VIF value greater than or equal to 5 or 10 shows significant multicollinearity and can be problematic for regression analysis, thus leading to invalid statistical interpretations (Jongh et al., 2015). Similarly, items with a VIF greater than 10 indicate that various parameters in a given model are not stable, resulting in an invalid interpretation of how a series of factors impact technology acceptance (Rad et al., 2022). From Table 6, it is visible that all items have VIF below 5, which indicates that no multicollinearity was observed among different factors in the model (Du & Lv, 2024)

Explanatory power of the model

The next step was to explain the explanatory power of the model by using R-squared and adjusted R-squared. R^2 values are between 0 and 1, and a higher value indicates higher explanatory power. Values of R-squared such as .25, .50, and .75 refer to weak, moderate, and higher explanation power. Similarly, Q^2 values above 0 are suggested, with a value of 0.0, .25, and .50 representing small, medium, and substantial effects (Ma, 2024). For

Table 7. Predictive relevance (Q^2) and Coefficient of determination (R^2).

	Q^2	R^2	R^2 adjusted
BI	.464	.593	.584
PEU	.408	.453	.428
PU	.478	.522	.512

behavioral intention (BI), the R-squared and adjusted R-squared values are .593 and .584 along with a Q-squared value of .464 respectively suggesting substantial strength of the model. Similarly, the R^2 and R^2 adjusted values of PU (.522, .512) show higher explanatory capacity as compared to PEU which can be considered as having moderate explanation power due to slightly low values of R-squared and adjusted R-squared. Overall, the model has high explanatory power as visible in Table 7.

Hypotheses testing and SEM

Table 8 delineates the relation between different factors and the intention of students' acceptance of (Gen) AI in English writing in their undergraduate studies. To compute the value of the path coefficient (beta value), the researcher utilized the PLS (Partial Least Square) algorithm. By using the PLS algorithm procedure, researchers can calculate the path coefficient value, also called the beta value, which shows the strength and weakness of the hypothesis' relation in SEM. To determine the significance level of the relation of different factors, researchers employed the bootstrapping technique with a default of 3000 iterations, which helps to measure the p-value.

Table 8. Result of the research hypothesis.

Hypothesis	Path	Beta value	T statistics	P values	Result
H1	PU -> BI	.606	6.024	0.000***	Accept
H2	PEU -> BI	.227	1.998	0.046*	Accept
H3	PEU -> PU	.456	5.132	0.000***	Accept
H4	AR -> PU	.378	4.178	0.000***	Accept
H5	OQ -> PU	.030	0.301	0.763	Reject
H6	GAISE -> PEU	–.073	0.685	0.493	Reject
H7	GAA ->PEU	–.036	0.401	0.689	Reject
H8	GAIP ->PEU	.332	3.320	0.001**	Accept
H9	PE -> PEU	.449	4.352	0.000***	Accept

Table 8 displays the result of PLS-SEM. Regarding academic relevance, the beta and p-value of ($\beta = .37$, p = 0.000***) indicates statistically positive and significant relation. In contrast, the hypothesis associated with output quality does not yield significant results ($\beta = 0.30$, p = 0.76); this suggests that the analyzed data doesn't provide strong evidence for the hypothesis. The hypothesis which shows the positive impact of perceived ease of use on perceived usefulness, suggests a strong relation as indicated by the beta value of (β =0.45). In addition, the observed value (p = 0.000*) indicates that the result is strongly significant.

The hypothesis related to (Gen) AI self-efficacy positive influence on perceived ease of use (PEU), suggests statistically opposite result. However, the analysis resulted in a negative result, which means that self-efficacy has a negative impact on perceived ease of use. The hypothesis associated with self-efficacy and perceived ease of use (PEU) reveals a non-significant result. The researcher established the positive influence of self-efficacy on perceived ease of use, however, the analysis resulted in negative relation. This is supported by path coefficient and observed values (β=-.073, p = 0.49). Similarly, the hypothesis which links the relation of GAA (Gen AI Anxiety) and PEU also reveals the same relation.

The beta value of ($\beta = -.036$) reflects a negative association between GAA and PEU. In addition, this is supported by the absence of statistical significance as confirmed by the probability value of (p=.68). Moreover, the hypothesis concerning the relationship of GAIP (Gen AI playfulness) and PEU demonstrates the result aligns with the already established hypothesis by the researchers. The beta value of ($\beta = 0.32$) reflects a positive link between GAIP and PEU. The relation is further strengthened by the significant value of the path coefficient. ($p = 0.01$). The hypothesis exploring the positive influence of PE on PEU reveals positive yet significant results. The path coefficient value of .44 suggests a positive correlation between participants' enjoyment of leveraging (Gen) AI and their perception of its ease of use.

The hypothesis, which reflects the positive influence of perceived usefulness on behavioral intention, shows a highly significant yet impactful result in the realm of students' acceptance of (Gen) AI in their English language writing. From Table 8, the beta value of .606 indicates a high positive association between perceived usefulness and behavioral intention. The prior relationship is statistically significant as validated by the p-value of 0.000***, reinforcing the vital role of perceived usefulness in shaping students' intention to leverage in their academic tasks in the future. Similarly, the hypothesis concerned with the relationship of perceived ease of use and behavioral intention reveals a strongly significant and positive relationship. The beta value of .227 suggests a moderate positive relation between perceived ease of use and behavioral intention, informing us that when students perceive (Gen) AI as easy to use, this results in their increase of adoption and utilization in the future. The association is statistically significant, as supported by the p-value of .046*.

In addition, Table 9 shows the goodness of model fit indices. It's of great significance that the researcher-designed model indicates a high standard of model fit. SRMR is one of the model fit indices, which measures model quality as how well the research model reflects the relationships in the analyzed data. An SRMR value closer to 0 suggests a good model fit, whereas a value greater than .08 is an indication of a poor model fit. Table 9 indicates the SRMR (Standard Mean Root Residual) value, which is below the standard threshold of .08.

Table 9. Goodness of model fit-indices.

Fit indices	Acceptable fit	Obtained fit	Reference
SRMR	$0.05 < \text{SRMR} \leq 0.10$	0.075	Yilmaz et al., 2023

Discussion and conclusion

The present study attempted to explore the varied factors influencing students' acceptance of (Gen) AI in their English writing grounded in the Technology Acceptance Model (TAM) 3 framework. The findings would provide critical insights for key factors of acceptance in English language pedagogy, thus reflecting the ever-evolving field of educational technology. On the basis of the results from PLS-SEM, six out of the eight hypotheses were supported by the current study except for three: output quality influence on perceived usefulness, (Gen) AI anxiety, and (Gen) AI self-efficacy impact on perceived ease of use. Most of the hypotheses were supported by this research, which underscores the robustness and validity of the modified research model in the context of (Gen) AI adoption in English writing. The current study identified three contradictory key findings, which can contribute to the existing literature in the realm of acceptance (Gen) AI in English writing.

The study didn't find support for the positive relation between output quality and perceived usefulness. The finding is also not consistent with previous studies (Zobeidi et al., 2023; Chaka, 2023; Papakostas et al., 2023) and the TAM framework. The Technology Acceptance Model (TAM) and its extensions, TAM2 and TAM3, consistently suggested that higher output quality results in greater perceived usefulness and results in technology adoption. However, the current findings suggest that contextual and sociocultural factors may shape students' perceptions differently. In Pakistan, academic institutions place strong emphasis on originality and individual academic effort, and concerns about plagiarism and academic integrity are frequently discussed in relation to emerging technologies. Students may therefore perceive AI-generated content as potentially problematic in academic settings even when the output appears linguistically sophisticated (Jabeen, 2023; Arshad et al., 2025; Arshad et al., 2026).

Another contextual factor relates to the sociolinguistic status of English in Pakistan. English occupies a prestigious position in the country's education system and is strongly associated with access to higher education, professional mobility, and social status (Rahman, 2020). Scholars have long noted that English functions as a marker of elite identity and educational privilege in Pakistan, shaping opportunities for academic and professional advancement (Irshad & Janjua, 2022; Syed, 2024). Consequently, English writing is often viewed not only as a functional academic skill but also as a demonstration of personal competence and intellectual ability.

The hypothesis associated with self-efficacy and perceived ease of use (PEU) reveals a notable finding. The research at hand hypothesized that self-efficacy positively influences students perceived ease of use in their English writing; however, the result showed negative influence. This suggests that as the self-efficacy to use (Gen) AI by students in English writing decreases, their perceptions of its ease of use increase, and that there is no evidence the data provide to support the hypothesis that lower self-efficacy is linked with maximum perceived ease of use in students' in their English writing. The finding of the study is in contrast with previous studies (Zhang et al., 2023; Thongsri et al., 2020; Jin, 2014; Kilic, 2014) as well as with the TAM theoretical framework. One of the possible reasons can be that students may possess the technological skills but still find tools, especially those relevant to their writing, complex and unpredictable in their overall function. This can stem from a lack of familiarity and structured training in the language education context (Ali et al., 2026). Although university students frequently use smartphones and social media platforms, formal training in emerging technologies such as AI-based writing tools is still limited in many institutions (Batool et al., 2025). Bandura (1997) suggested that context-specific self-efficacy is prone to task difficulty; as a result, higher self-efficacy might not result in perceived ease of use if students are not familiar with prompt engineering, tools and their functions, and editing AI-generated content. Furthermore, traditional teacher-centered pedagogical practices in many Pakistani universities may limit students' opportunities to experiment independently with emerging technologies (Rehman et al., 2025).

The present study did not support the hypothesized negative relationship between anxiety and perceived ease of use. This finding contrasts with earlier studies reporting that technology anxiety reduces perceived ease of use (Abdullah et al., 2016; Islamoglu et al., 2021; Zhang et al., 2023). However, it is consistent with emerging evidence suggesting that AI anxiety may positively influence technology adoption under certain conditions. For instance, Chen et al. (2025) found that AI anxiety enhances students' willingness to engage with AI through increased perceived value. A possible explanation is the distinction between computer anxiety and AI anxiety. Unlike computer anxiety, which is often associated with low self-efficacy and negative attitudes toward technology (Day & Mäkirinne Crofts, 1997), AI anxiety may motivate students to acquire AI-related competencies that are increasingly viewed as essential for academic and professional success (Wang & Wang, 2019; Zhang et al., 2023). Institutional support, including instructor guidance, workshops, and peer collaboration, may further reduce apprehension and enable students to perceive GenAI tools as easier to use (Saade & Kira, 2007).

This explanation is particularly relevant in the Pakistani context, where the growing digital economy and technology-driven employment opportunities have increased the importance of AI and digital literacy (Qureshi et al., 2025; Shamsi et al., 2025). As universities increasingly integrate technology-enhanced learning, students are more likely to engage with AI applications despite initial uncertainty, gradually improving their perceptions of ease of use (Ikram et al., 2025; Khan et al., 2025). These findings are further supported by previous research highlighting the pedagogical value of AI in language education. Afzaal et al. (2020) emphasized AI's role in personalized and context-sensitive language learning, Imran & Almusharraf (2025) stressed the importance of effective pedagogical integration of educational innovations, and Bashir et al. (2025) demonstrated that technology-enhanced pedagogy improves learner motivation and willingness to communicate.

In conclusion, the study supported six of the nine proposed TAM 3 hypotheses. Academic relevance and perceived ease of use significantly predicted perceived usefulness, whereas GenAI playfulness and perceived enjoyment emerged as the strongest determinants of perceived ease of use. Furthermore, both perceived usefulness and perceived ease of use significantly influenced students' behavioral intention to adopt GenAI for English writing, with perceived usefulness exerting the stronger effect.

Implications

The findings of the study may provide preliminary insights for the factor influencing students' acceptance of in English writing within the Technology Acceptance Model (TAM) 3 framework. The present study extends TAM 3 to the English writing context, thus offering novel insights into how language learners engage with new technologies in discipline-specific learning. The model-fit indices of the model show that it can be integrated beyond English writing, as the model is a technology model. The findings of this study have several important implications for English language pedagogy, educational policy, and technology integration in higher education.

The strong influence of perceived usefulness on behavioral intention highlights the need for language educators to clearly demonstrate the academic benefits of tools in English writing instruction. Curriculum designers should embed supported writing tasks that align with clear learning outcomes and performance criteria.

The study found novel evidence for (Gen) AI anxiety, as anxiety can be positively associated with perceived ease of use, highlighting that anxiety under certain circumstances may work as a motivator rather than a hindrance. By highlighting the negative association between output quality of (Gen) AI and perceived ease of use, the current study challenges the assumption that technical performance does not solely determine students' acceptance of (Gen) AI; rather, content relevance and students' academic expectations also play a vital role.

The non-significant relationship between self-efficacy and perceived ease of use challenges the assumption that confidence always translates into ease. This suggests that even confident students may find certain features non-intuitive or contextually misaligned with academic writing tasks. Language educators should thus focus not only on fostering confidence but also on ensuring that tools are pedagogically appropriate and cognitively aligned with learners' goals.

The present study was limited to one public university, Air University, Pakistan, which limits the overall generalizability of the findings to other higher educational institutions. However, it can be generalized to some degree in the Pakistani culture, as the target institution is similar to other higher institutes in Pakistani university systems in terms of students' age, learning environment, and accessibility to technologies. Although the study was restricted to one university, it consisted of participants from different departments and disciplines to enhance representativeness and reduce the risk of disciplinary bias. Future research should extend the number of institutions to a wide range to enhance the relevance of the findings across various educational and cultural contexts. This study leverages a cross-sectional survey questionnaire that explores students' acceptance of (Gen) AI English writing at a specific timeframe. Such a design doesn't likely fully measure the students' acceptance level, as their use of (Gen) AI might alter over time, thus requiring longitudinal studies to fully capture how students' acceptance evolves as they get more experienced. However, the data from the students was collected after they had meaningful interaction with (Gen) AI, thus allowing reflective responses. The present study focused on students' insights of and their acceptence of (Gen) AI English writing, which can provide a single perspective. Future research can investigate students', teachers', and administrators' perspectives for comprehensive insights. In addition, future studies can compare the prior perspectives and identify where the acceptance ratio was high and low and why.

Conflict of interest

The authors declare no conflict of interest.

Author contribution

Ikram Ullah: Conceptualization, methodology, investigation, formal analysis, writing—original draft, project administration.

Huma Batool: Conceptualization, methodology, data curation, validation, writing—review and editing, supervision.

Sadia Irshad: Conceptualization, supervision, writing—review and editing.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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