



Determinants of students’ decision to adopt generative ai in higher education: an extended technology acceptance model with information quality

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Article Information	Abstract
Submitted: Jan 17, 2026 Revised: March 23, 2026 Accepted: May 05, 2026	Purpose: This study examines the determinants influencing students’ decisions to adopt Generative Artificial Intelligence (GenAI) in higher education by extending the Technology Acceptance Model (TAM) with the inclusion of information quality. Method: A quantitative approach was employed through an online survey targeting university students who have experience using GenAI tools. A total of 204 valid responses were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess both the measurement and structural relationships among variables. Findings: The findings reveal that perceived usefulness, perceived ease of use, enjoyment, self-efficacy, and information quality significantly influence students’ decisions to adopt GenAI. Among these factors, perceived usefulness and information quality demonstrate the strongest effects. Conversely, computer anxiety does not show a significant influence on adoption decisions. Significance: This study contributes to the existing literature by integrating information quality into an extended TAM framework, providing a more comprehensive perspective on decision-making in the adoption of emerging AI technologies. The results offer practical implications for higher education institutions and developers to enhance adoption by improving usability, user competence, and the reliability of AI-generated information.

INTRODUCTION

The rapid advancement of digital technology has significantly transformed various sectors, including higher education systems. Information technology is increasingly integrated into learning environments to enhance efficiency, accessibility, and student engagement (Ghanbaripour et al., 2024; Pandita & Kiran, 2023; Ullah & Anwar, 2020). One of the most recent and impactful innovations is Generative Artificial Intelligence (GenAI), which has gained widespread attention globally (Kanbach et al., 2024; Sedkaoui & Benaichouba, 2024; Storey et al., 2025). GenAI systems are capable of generating human-like outputs such as text, images, and data through advanced machine learning techniques (Ferrara, 2024; Yang et al., 2025). The accessibility of these tools has enabled students to utilize them as supportive instruments in academic activities. As a result, learning processes are becoming more adaptive, personalized, and efficient. The increasing adoption of GenAI reflects a shift toward technology-driven education models. In many higher education institutions, students actively use GenAI to assist with problem-solving, content generation, and information retrieval. This growing reliance indicates that GenAI is becoming an integral component of modern learning practices. Therefore, understanding how students interact with and perceive GenAI is essential in evaluating its role in educational transformation.

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In the context of higher education, the integration of GenAI offers both opportunities and challenges for students and institutions. On the one hand, GenAI enhances learning efficiency by providing rapid access to information and supporting academic tasks (Gökoğlu & Erdoğan, 2025; Kangwa et al., 2025; Monzon & Hays, 2025). It also enables personalized learning experiences tailored to individual student needs and preferences. On the other hand, concerns have emerged regarding academic integrity, over-reliance on AI tools, and reduced critical thinking skills (Al-Hajaya, 2025; Zhai et al., 2024). Some institutions have raised issues related to plagiarism and the authenticity of student work generated using GenAI. In addition, educators face challenges in assessing students' actual understanding when AI tools are used extensively. These concerns highlight that the adoption of GenAI is not purely based on its functional benefits. Instead, it involves complex behavioral and cognitive processes that influence students' decisions to use such technologies. Consequently, it is important to analyze the determinants that shape students' adoption behavior. Understanding these factors can help institutions design strategies to optimize the use of GenAI in education. Thus, a comprehensive evaluation of adoption behavior is necessary to balance its benefits and risks.

Another important issue in the adoption of GenAI is the quality of information generated by these systems. Although GenAI can produce fast and contextually relevant responses, it may also generate inaccurate or misleading information (Ferrara, 2024; Fulsher et al., 2026). In educational settings, information accuracy and reliability are critical for effective learning outcomes. Students who rely on incorrect information may develop misconceptions that affect their academic performance (C. Chen et al., 2020; Siantuba et al., 2023; Vieriu & Petrea, 2025). Therefore, information quality plays a crucial role in shaping user trust and decision-making behaviour. Previous studies have highlighted that system-related factors such as usability and usefulness influence technology adoption. However, the role of information quality in AI-based systems remains less explored compared to traditional information systems. Given the unique characteristics of GenAI, the evaluation of information quality becomes increasingly important. The uncertainty associated with AI-generated content may influence students' perceptions and decision. As a result, incorporating information quality into technology acceptance models can provide a more comprehensive understanding. Hence, examining the interplay between technological and informational factors is essential in explaining GenAI adoption.

A growing body of literature has examined the adoption and acceptance of artificial intelligence (AI) technologies across various domains, including organizational settings, social media, healthcare, and emerging digital environments such as the metaverse, with many studies relying on the Technology Acceptance Model (TAM) and its extensions to explain user behavior (Al-Qaysi et al., 2020; Kamal et al., 2020; Sagnier et al., 2020; Wu et al., 2024). In recent years, research has also expanded toward AI adoption and decision-making processes, highlighting the influence of factors such as readiness, trust, and system-related characteristics in shaping adoption behavior (Khanfar et al., 2025; Marocco et al., 2024; Polisetty et al., 2024). Within the educational context, studies have emphasized the transformative potential of Generative Artificial Intelligence (GenAI) in enhancing learning experiences and supporting academic activities, yet these studies are

predominantly conceptual or descriptive and lack empirical validation of user behavior (Mao et al., 2024; Samala et al., 2025; Yu & Guo, 2023). Moreover, existing research on AI and TAM largely focuses on general acceptance or behavioral intention, rather than explicitly conceptualizing adoption as a decision-making process, particularly among students in higher education. In addition, although prior studies acknowledge the importance of system and data-related factors, the role of information quality especially in the context of AI-generated content that may be inaccurate or misleading remains insufficiently explored and rarely integrated into TAM-based models (Bondac et al., 2026; Kharchenko et al., 2022; Thekdi & Aven, 2025). Therefore, a clear research gap exists in developing a comprehensive framework that integrates technological perceptions, decision-making behavior, and information quality to better explain students' decisions to adopt Generative AI in higher education.

Based on the aforementioned background, this study aims to analyze the determinants influencing students' decisions to adopt Generative Artificial Intelligence in higher education. This research extends the Technology Acceptance Model (TAM) by incorporating information quality as an additional construct. The study seeks to provide a more comprehensive framework that integrates technological, behavioral, and informational factors. A quantitative approach is employed to examine the relationships between key variables affecting adoption decisions. The model includes constructs such as perceived usefulness, perceived ease of use, enjoyment, self-efficacy, and information quality. By focusing on decision-making behavior, this study moves beyond traditional acceptance perspectives. The findings are expected to contribute to the theoretical development of technology adoption models. In addition, the study aims to provide empirical evidence within the context of higher education. The results are also intended to offer practical insights for institutions and developers in improving GenAI implementation. Ultimately, this research seeks to support more effective and responsible use of GenAI in educational environments.

LITERATURE REVIEW

The rapid development of artificial intelligence has led to the emergence of Generative Artificial Intelligence (GenAI) as a transformative technology in various sectors, including education. GenAI refers to a class of AI systems capable of generating new content such as text, images, and multimedia outputs based on learned data patterns. In educational contexts, GenAI has been increasingly utilized as a tool to support learning activities and academic tasks (Daher & Hussein, 2024; Ng et al., 2025). Students use these technologies to assist in writing, summarizing information, solving problems, and exploring new knowledge. The integration of GenAI into learning environments contributes to more flexible and personalized educational experiences (Anderson et al., 2025; Hu & Shao, 2025). This shift aligns with the broader trend of digital transformation in higher education systems. However, the adoption of GenAI is not solely determined by technological availability. Users' perceptions, attitudes, and experiences significantly influence how these technologies are utilized. Therefore, understanding behavioral aspects of GenAI adoption is essential in educational research. This highlights the need for theoretical frameworks that can explain user behavior in adopting emerging technologies.

One of the most widely used frameworks for analyzing user behavior toward technology adoption is the Technology Acceptance Model (TAM). TAM explains how users come to accept and use a technology based on two primary constructs, namely perceived usefulness and perceived ease of use (L. Chen & Aklikokou, 2020). Perceived usefulness refers to the degree to which a user believes that using a particular system will enhance performance. Meanwhile, perceived ease of use relates to the extent to which a system is perceived as free of effort. These constructs influence users' attitudes, which subsequently affect their behavioral intentions and actual system use. TAM has been extensively applied across various domains, including education, healthcare, and information systems (Alsyoud et al., 2023; Kalayou et al., 2020; Lee et al., 2025; Zin et al., 2023). The model is particularly suitable for analyzing new technologies that are still in the early stages of adoption. Over time, researchers have expanded TAM to include additional variables that better capture complex user behavior. These extensions aim to improve the explanatory power of the model in different contexts. As a result, TAM remains a dominant framework for studying technology adoption.

In recent years, the extended TAM has incorporated various external factors such as enjoyment, self-efficacy, experience, and computer anxiety to better explain user behavior. Enjoyment reflects the intrinsic motivation of users when interacting with a system, which can influence their willingness to adopt technology (Gupta, 2019; Sun & Gao, 2020; Vanduhe et al., 2020; Won et al., 2022). Self-efficacy represents users' confidence in their ability to use technological systems effectively (Alnoor et al., 2020; Saville & Foster, 2021; Shao et al., 2025; Xu et al., 2024). Experience is another important factor that shapes familiarity and reduces uncertainty in technology use. On the other hand, computer anxiety may negatively affect users' perceptions and limit their adoption behavior. These variables provide a more comprehensive understanding of the psychological and behavioral dimensions of technology use. In the context of emerging technologies, these factors become increasingly relevant due to the novelty and complexity of the systems (Kumar et al., 2021; Tomassi et al., 2025). Previous studies have demonstrated that extended TAM models offer better predictive accuracy compared to the original model. Therefore, incorporating additional variables is necessary to capture the multifaceted nature of user adoption behavior. This approach is particularly important when analyzing technologies such as GenAI.

Beyond technological and behavioral factors, the quality of information generated by AI systems has become a critical concern. Information quality refers to the accuracy, relevance, completeness, and timeliness of the information provided by a system. In traditional information systems, high information quality is associated with increased user satisfaction and continued system use (Alyoussef, 2023; Masri et al., 2019; Shim & Jo, 2020). However, in the case of GenAI, the issue of information quality becomes more complex due to the probabilistic nature of generated outputs. GenAI systems may produce responses that appear plausible but contain inaccuracies or inconsistencies. This characteristic raises concerns about the reliability of AI-generated content, especially in academic contexts. Students relying on such information may face risks related to misinformation and misunderstanding. Consequently, information quality plays a crucial role in shaping trust and decision-making processes. Despite its importance, information

quality has not been widely integrated into TAM-based studies in the context of GenAI. This gap suggests the need to incorporate information quality into adoption models. Doing so can provide a more comprehensive understanding of user behavior in AI-driven environments.

Furthermore, recent studies have begun to emphasize the importance of decision-making processes in technology adoption. Adoption is not merely a passive acceptance but involves active evaluation and judgment by users. Decision-making in technology use is influenced by cognitive, emotional, and contextual factors. In the context of GenAI, students must evaluate both the benefits and potential risks associated with its use. Factors such as perceived usefulness, trust, and information reliability contribute to these decisions. The concept of decision to adopt extends beyond behavioral intention by emphasizing actual user choices. This perspective aligns with the growing interest in behavioral decision theory within technology adoption research. However, limited studies have explicitly examined adoption as a decision-making process in educational settings. Most research still focuses on intention rather than actual decision behavior. Therefore, integrating decision-making perspectives into TAM provides a more nuanced understanding of technology adoption. This study addresses this gap by analyzing students' decision to adopt GenAI using an extended TAM framework that includes information quality.

METHOD

Research Design

This study employed a quantitative research design to examine the determinants influencing students' decisions to adopt Generative Artificial Intelligence (GenAI) in higher education. A cross-sectional survey approach was used to collect data at a single point in time. The research model was developed based on the extended Technology Acceptance Model (TAM) with the inclusion of information quality as an additional construct. The model incorporates multiple variables, including perceived usefulness, perceived ease of use, enjoyment, self-efficacy, computer anxiety, and information quality. The study focuses on identifying the relationships between these variables and students' decision to adopt GenAI. A structured questionnaire was used as the primary data collection instrument. The design allows for empirical testing of hypotheses using statistical modeling techniques. The quantitative approach was selected due to its suitability for measuring perceptions and behavioral intentions. This design also enables the generalization of findings within the study context. Therefore, the research design provides a systematic framework for analyzing user adoption behavior.

Participants

The participants in this study consisted of university students who have experience using Generative Artificial Intelligence tools. The target population was students enrolled in higher education institutions. A purposive sampling technique was applied to ensure that respondents had prior exposure to GenAI platforms. A total of 204 valid responses were obtained and used for data analysis. The sample size is considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. Participants were drawn from various academic disciplines to ensure diversity in responses. The inclusion criteria required respondents to have used at least one GenAI platform, such as text-based

or AI-assisted tools. This approach ensures that participants have relevant experience in evaluating the technology. The demographic characteristics of participants include variations in gender, academic level, and usage frequency. These characteristics provide contextual insights into user behavior. Overall, the selected participants represent a relevant group for examining GenAI adoption in higher education.

Instruments

Data were collected using a structured questionnaire designed based on validated constructs from previous studies on TAM and its extensions. The questionnaire consisted of multiple items measuring each variable in the research model. All items were adapted and modified to fit the context of Generative Artificial Intelligence in education. A Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to measure respondents' perceptions. The instrument included sections covering demographic information and core research variables. Prior to data collection, the questionnaire was reviewed to ensure clarity and relevance. Data collection was conducted through an online survey platform to facilitate wider participation. The use of online distribution enabled efficient data gathering within a limited timeframe. Respondents voluntarily participated in the study and completed the questionnaire independently. Data screening was performed to ensure completeness and validity of responses. Only valid and complete responses were included in the final dataset.

Data Analysis

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the support of SmartPLS software. PLS-SEM was selected due to its ability to analyze complex models with multiple constructs and indicators. The analysis process consisted of two main stages, namely the evaluation of the measurement model and the structural model. The measurement model was assessed through reliability and validity tests, including composite reliability, Cronbach's alpha, and average variance extracted (AVE). Convergent and discriminant validity were also evaluated to ensure the accuracy of the measurement model. The structural model was examined by analyzing path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Hypothesis testing was conducted using bootstrapping procedures to determine the significance of relationships between variables. This approach allows for robust estimation of model parameters. The results provide insights into the strength and direction of relationships among constructs. Therefore, PLS-SEM is appropriate for testing the proposed research model.

Procedure

The research procedure began with an extensive literature review to identify relevant variables and develop the research model. Based on the literature, hypotheses were formulated to describe the relationships between constructs. The questionnaire was then developed and refined before being distributed to participants. Data collection was conducted over a specified period using an online survey method. After data collection, responses were screened to remove incomplete or invalid entries. The cleaned dataset was then prepared for statistical analysis. The measurement model was first evaluated to ensure reliability and validity. Subsequently, the structural model was analyzed to test the

proposed hypotheses. The findings were interpreted to identify key determinants influencing students' adoption decisions. Finally, conclusions and implications were drawn based on the analysis results. This procedure ensures a systematic and rigorous approach to achieving the research objectives.

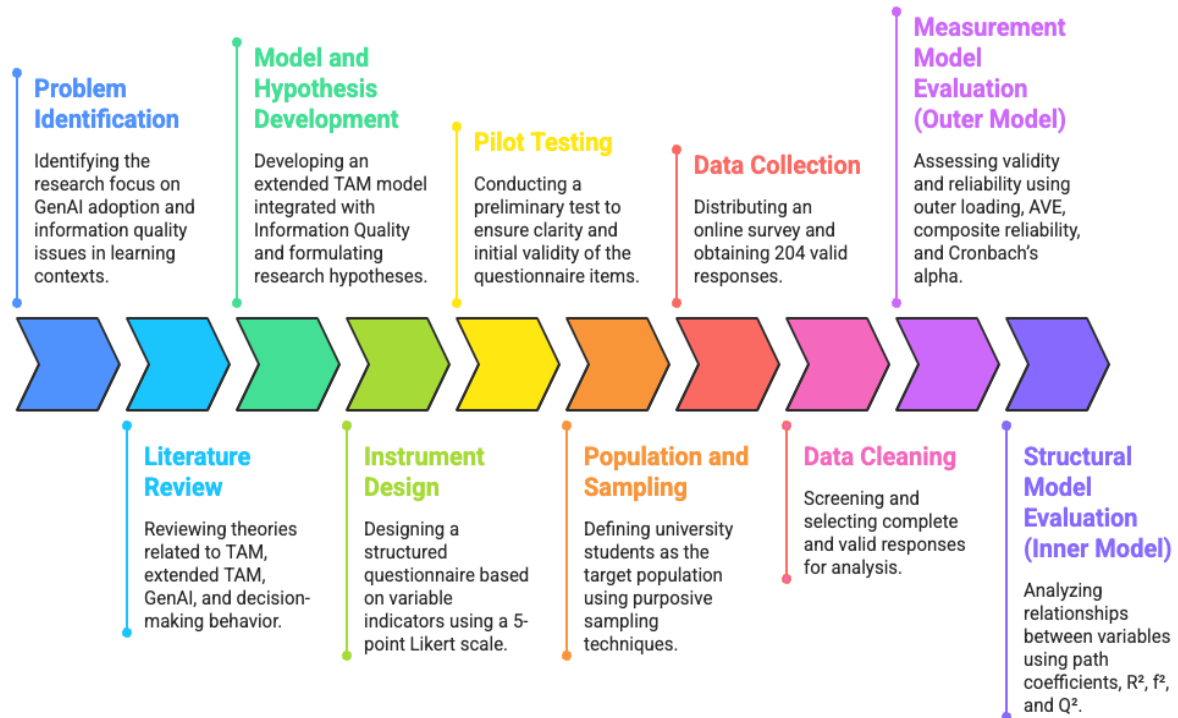


Figure 1. Research Procedure Flowchart

RESULTS AND DISCUSSION

Result

Respondent Characteristics

A total of 204 valid responses were included in the final analysis after data screening. All respondents were university students who had prior experience using Generative Artificial Intelligence (GenAI) tools in academic contexts. The purposive sampling approach ensured that only individuals with relevant exposure to GenAI were selected. The respondents represented diverse academic backgrounds, indicating heterogeneity in educational disciplines. Variations were also observed in the frequency and duration of GenAI usage, suggesting different levels of familiarity with the technology. Most respondents reported regular interaction with GenAI platforms, particularly for tasks such as information retrieval, content generation, and academic assistance. This indicates that the sample is appropriate for examining adoption behavior. The use of an online questionnaire enabled broad participation and efficient data collection. The dataset was carefully screened to remove incomplete or inconsistent responses. Only fully completed questionnaires were retained for analysis. Therefore, the final dataset is considered valid and reliable for subsequent statistical evaluation.

Table 1. Respondent profile summary

Category	Description
Total respondents	204
Target group	University students
Sampling technique	Purposive sampling
Experience with GenAI	All respondents have prior experience
Data collection method	Online questionnaire

Measurement model evaluation (outer model)

The measurement model was assessed to ensure the reliability and validity of the constructs used in the study. Indicator reliability was evaluated through outer loading values, where all indicators exceeded the recommended threshold of 0.70. This indicates that each item adequately represents its respective construct. Internal consistency reliability was confirmed through Cronbach's Alpha and Composite Reliability values, both of which were above 0.70. These results suggest that the measurement scales are consistent and stable. Convergent validity was examined using the Average Variance Extracted (AVE), and all constructs achieved values greater than 0.50. This demonstrates that the constructs explain more than half of the variance of their indicators. Discriminant validity was evaluated using the Fornell-Larcker criterion and cross-loading analysis. The results indicate that each construct is distinct from the others. No multicollinearity issues were detected among the indicators. Overall, the measurement model satisfies all required criteria. Therefore, it is appropriate to proceed with structural model evaluation.

Table 2. Measurement model results

Construct	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
Perceived Usefulness	> 0.70	> 0.70	> 0.80	> 0.50
Perceived Ease of Use	> 0.70	> 0.70	> 0.80	> 0.50
Enjoyment	> 0.70	> 0.70	> 0.80	> 0.50
Self-Efficacy	> 0.70	> 0.70	> 0.80	> 0.50
Information Quality	> 0.70	> 0.70	> 0.80	> 0.50
Computer Anxiety	> 0.70	> 0.70	> 0.80	> 0.50

Structural model evaluation (inner model)

The structural model was analyzed to examine the relationships between latent variables in the proposed framework. The coefficient of determination (R^2) was used to assess the explanatory power of the model. The R^2 value for the intention to adopt variable indicates a moderate to strong level of explained variance. This suggests that the independent variables included in the model effectively explain the dependent construct. Effect size (f^2) values were calculated to evaluate the relative impact of each predictor. The results indicate that perceived usefulness and information quality have relatively strong effects compared to other variables. Predictive relevance (Q^2) values were also assessed using the blindfolding procedure. The Q^2 values were greater than zero, indicating that the model has predictive relevance. The path coefficients provide information on the direction and strength of relationships among variables. All key paths show positive relationships, except those involving computer anxiety. The structural model results confirm that the proposed framework is statistically adequate. Therefore, the model is suitable for hypothesis testing.

Table 3. structural model results

Variable	R ²	Effect Size (f ²)	Predictive Relevance (Q ²)
Perceived Usefulness	Moderate	Medium-High	> 0
Perceived Ease of Use	Moderate	Medium	> 0
Intention to Adopt	High	High	> 0

Hypothesis testing

Hypothesis testing was conducted using the bootstrapping procedure to evaluate the significance of relationships between variables. The results indicate that the majority of the proposed hypotheses are supported. Perceived usefulness has a significant positive effect on intention to adopt, indicating its central role in decision-making. Perceived ease of use significantly influences perceived usefulness and attitude toward use. Enjoyment and self-efficacy also show positive and significant relationships with both perceived usefulness and perceived ease of use. Information quality emerges as a strong predictor, particularly influencing perceived usefulness and perceived ease of use. These findings highlight the importance of informational factors in technology adoption. In contrast, computer anxiety does not show a significant effect on either perceived usefulness or perceived ease of use. This suggests that students are generally not hindered by anxiety when using GenAI tools. The results provide empirical support for the extended TAM model used in this study. Therefore, the majority of relationships in the model are statistically validated.

Table 4. Hypothesis testing results

Hypothesis	Relationship	Result
H1	Experience → Perceived Usefulness	Supported
H2	Experience → Perceived Ease of Use	Supported
H3	Enjoyment → Perceived Usefulness	Supported
H4	Enjoyment → Perceived Ease of Use	Supported
H5	Computer Anxiety → Perceived Usefulness	Not Supported
H6	Computer Anxiety → Perceived Ease of Use	Not Supported
H7	Self-Efficacy → Perceived Usefulness	Supported
H8	Self-Efficacy → Perceived Ease of Use	Supported
H9	Information Quality → Perceived Usefulness	Supported
H10	Information Quality → Perceived Ease of Use	Supported
H11	Perceived Ease of Use → Perceived Usefulness	Supported
H12	Perceived Ease of Use → Attitude	Supported
H13	Perceived Usefulness → Attitude	Supported
H14	Perceived Usefulness → Intention	Supported
H15	Attitude → Intention	Supported
H16	Intention → Actual Use	Supported

The results indicate that both technological and informational factors significantly influence students' decisions to adopt GenAI. Perceived usefulness is identified as a key determinant, reflecting its central role in user evaluation of technology. Information quality also demonstrates a strong influence, highlighting its importance in AI-based systems. Perceived ease of use contributes indirectly by influencing perceived usefulness. Behavioral factors such as enjoyment and self-efficacy positively support adoption decisions. The absence of significant influence from computer anxiety suggests a high level of user familiarity with digital technologies. The model explains a substantial proportion

of variance in adoption behavior. The findings confirm the robustness of the extended TAM framework. Overall, the results provide a comprehensive understanding of adoption behavior. These findings serve as a foundation for further discussion and interpretation.

Discussion

The findings of this study confirm that perceived usefulness plays a dominant role in influencing students' decisions to adopt Generative Artificial Intelligence (GenAI) in higher education. This result aligns with prior studies emphasizing that perceived usefulness is a key determinant in technology adoption across educational contexts. Previous research consistently demonstrates that when users perceive a technology as beneficial for improving performance, they are more likely to adopt it (Al-Maatouk et al., 2020; Caffaro et al., 2020; FakhrHosseini et al., 2024; Ma et al., 2025). In the context of GenAI, usefulness is often associated with efficiency in completing academic tasks and improving learning outcomes (Alkabaa & Alamri, 2025; Alotaibi, 2025; Nikolic et al., 2024). This study further strengthens this argument by showing that perceived usefulness significantly influences both attitude and intention to adopt. Similar findings have been reported in studies applying TAM and UTAUT models in AI adoption research. However, compared to earlier studies, this research highlights the stronger predictive role of perceived usefulness in decision-making rather than mere behavioral intention. This suggests that GenAI adoption is not only driven by perception but also by rational evaluation of benefits. The findings also indicate that usefulness remains relevant even in highly advanced AI systems. Therefore, perceived usefulness continues to be a central construct in understanding GenAI adoption behavior.

In addition to perceived usefulness, perceived ease of use also demonstrates a significant influence on adoption behavior. This finding is consistent with the foundational assumptions of TAM, where ease of use affects both perceived usefulness and user attitudes (Liesa-Orús et al., 2023). Previous studies have shown that systems that are easier to use tend to increase user satisfaction and adoption rates. In the context of GenAI, ease of use relates to intuitive interfaces and accessibility of tools. Empirical evidence suggests that user-friendly AI systems enhance engagement and reduce cognitive effort (Feng, 2025; Virvou, 2023). This study confirms that ease of use indirectly influences adoption decisions through perceived usefulness. Such indirect effects have also been reported in extended TAM studies across digital learning environments. However, the magnitude of its effect is lower compared to perceived usefulness, indicating that users prioritize outcomes over effort. This finding supports the argument that users are willing to tolerate complexity if the benefits are substantial. Moreover, it reflects the increasing digital literacy among students, which reduces the barrier of system complexity. Therefore, ease of use remains an important but secondary factor in GenAI adoption.

The results also reveal that behavioral factors such as enjoyment and self-efficacy significantly influence students' adoption decisions. This finding is consistent with extended TAM research that incorporates psychological constructs to explain user behavior (Hsu & Lin, 2022; Li et al., 2025; Mailizar et al., 2021). Enjoyment reflects intrinsic motivation, which has been shown to enhance technology acceptance in learning environments (An et al., 2024; David & Weinstein, 2024; Man et al., 2026; Vanduhe et al., 2020). Previous studies indicate that enjoyable learning experiences increase engagement

and willingness to adopt new technologies. Similarly, self-efficacy influences users' confidence in using technological tools effectively. Empirical studies have demonstrated that higher self-efficacy leads to stronger adoption intentions in digital learning systems. This study confirms that both variables positively affect perceived usefulness and perceived ease of use. Compared to prior research, the role of self-efficacy appears particularly important in the context of GenAI due to its perceived complexity. Additionally, enjoyment contributes to reducing resistance to adopting new technologies. These findings highlight that adoption is not solely driven by cognitive factors but also by emotional and psychological influences. Therefore, incorporating behavioral constructs provides a more comprehensive explanation of GenAI adoption.

One of the most significant contributions of this study is the identification of information quality as a key determinant in GenAI adoption. The findings indicate that information quality significantly influences both perceived usefulness and perceived ease of use. This result supports previous research emphasizing the importance of reliable and accurate information in technology adoption. In the context of GenAI, concerns about misinformation and inaccuracies have been widely reported. Unlike traditional systems, GenAI produces probabilistic outputs that may not always be accurate. This study extends prior research by demonstrating that information quality plays a critical role in shaping decision-making behavior. Previous studies have often focused on system quality rather than information quality. However, this research shows that content reliability is equally important in AI-based systems. The findings also highlight that students are sensitive to the credibility of AI-generated information. This sensitivity influences their evaluation and decision to adopt the technology. Therefore, integrating information quality into TAM provides a more robust framework for understanding GenAI adoption.

Interestingly, the results show that computer anxiety does not significantly influence adoption behavior. This finding contrasts with earlier studies where anxiety was identified as a barrier to technology adoption. One possible explanation is the increasing familiarity of students with digital technologies. Modern students are often exposed to various digital tools from an early age, reducing their level of technological anxiety. Similar findings have been reported in recent AI adoption studies, where anxiety has diminished as a significant predictor. This indicates a shift in user behavior in the digital era. Furthermore, the non-significant effect of anxiety suggests that GenAI tools are perceived as accessible and user-friendly. This may also reflect improvements in interface design and usability of modern AI systems. Compared to earlier generations of technology, current systems require less technical expertise. Therefore, anxiety is no longer a dominant factor in adoption decisions. This finding suggests that future research may focus more on cognitive and informational factors rather than emotional barriers.

Implication

The findings of this study offer important theoretical and practical implications for understanding the adoption of Generative Artificial Intelligence (GenAI) in higher education. From a theoretical perspective, this study extends the Technology Acceptance Model (TAM) by incorporating information quality as a critical determinant, thereby enhancing the explanatory power of the model in the context of emerging AI technologies. The integration of information quality provides a more comprehensive framework that

captures both technological and informational dimensions of user decision-making. This contribution is particularly relevant given the unique characteristics of GenAI, where output reliability directly influences user trust and adoption behavior. From a practical standpoint, the results highlight the importance of improving perceived usefulness to encourage student adoption of GenAI tools. Educational institutions should focus on demonstrating the tangible benefits of GenAI in supporting academic performance and learning efficiency. Additionally, enhancing system usability remains essential to ensure that students can easily interact with AI tools without significant effort. The significant role of self-efficacy suggests that training programs and digital literacy initiatives can improve students' confidence in using GenAI effectively. Furthermore, the influence of enjoyment indicates that user experience design should prioritize engagement and interactivity. The strong effect of information quality emphasizes the need for developers to improve the accuracy, consistency, and reliability of AI-generated content. Institutions should also establish guidelines to ensure responsible and ethical use of GenAI in academic settings. Overall, these implications provide valuable insights for stakeholders to optimize the implementation and adoption of GenAI in higher education environments.

Limitation and Suggestion for Further Research

This study has several limitations that should be acknowledged to provide context for interpreting the findings. First, the use of a cross-sectional research design limits the ability to capture changes in students' adoption behavior over time. Future research could employ longitudinal approaches to better understand how perceptions and decisions evolve with continued exposure to Generative Artificial Intelligence (GenAI). Second, the study relies on self-reported data collected through questionnaires, which may be subject to response bias or social desirability effects. Further studies may incorporate behavioral data or system usage logs to validate user responses. Third, the sample is limited to university students, which may restrict the generalizability of the findings to other user groups such as educators or professionals. Expanding the sample to include diverse populations would enhance the external validity of the results. Fourth, this study focuses on selected variables within the extended Technology Acceptance Model (TAM), and other relevant factors such as trust, perceived risk, and ethical concerns were not included. Future research could integrate these variables to develop a more comprehensive model of GenAI adoption. Additionally, the rapid evolution of GenAI technologies may influence user perceptions differently over time, suggesting the need for continuous empirical investigation. The study also does not differentiate between types of GenAI tools, which may vary in functionality and user experience. Future studies could conduct comparative analyses across different AI platforms to identify variations in adoption behavior. Moreover, cultural and institutional factors were not explicitly examined, which may influence decision-making in different educational contexts. Therefore, future research should consider cross-cultural and multi-institutional studies to provide broader insights. Overall, addressing these limitations will contribute to a deeper and more robust understanding of GenAI adoption in higher education.

CONCLUSION

This study investigated the determinants influencing students' decisions to adopt Generative Artificial Intelligence (GenAI) in higher education using an extended Technology Acceptance Model (TAM). The findings demonstrate that perceived usefulness plays a central role in shaping students' adoption decisions, confirming its importance in evaluating emerging technologies. Perceived ease of use also contributes significantly, primarily through its influence on perceived usefulness and user attitudes. Behavioral factors, including enjoyment and self-efficacy, were found to positively affect students' perceptions and their willingness to adopt GenAI. These results highlight the importance of both cognitive and psychological dimensions in technology adoption. A key contribution of this study is the inclusion of information quality, which was shown to significantly influence both perceived usefulness and perceived ease of use. This finding emphasizes that the reliability and accuracy of AI-generated content are critical in shaping adoption decisions. In contrast, computer anxiety was found to have no significant impact, suggesting that students are generally comfortable using advanced digital technologies. The overall model demonstrates strong explanatory power in predicting students' adoption behavior. These findings provide empirical support for extending TAM to better capture the dynamics of AI-based systems. The study contributes to the growing body of literature on GenAI adoption in educational contexts. Ultimately, this research provides a comprehensive understanding of how technological, behavioral, and informational factors interact in influencing students' decisions to adopt GenAI.

AUTHOR CONTRIBUTIONS STATEMENT

RPS : Conceptualization, research design, instrument development, data collection, data analysis, and drafting the original manuscript.

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