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Perceptions and institutional readiness for generative AI adoption in education using a multi-method approach

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ABSTRACT

The rapid emergence of generative artificial intelligence (GenAI) tools like ChatGPT is reshaping educational practices, presenting both transformative opportunities and institutional challenges. This study offers a novel, integrative framework for understanding the adoption of GenAI tools in higher education by combining quantitative and qualitative analyses within a hybrid methodological design. Specifically, it is the first to incorporate the analytical hierarchy process (AHP), fuzzy decision-making trial and evaluation laboratory (Fuzzy DEMATEL), and the extended technology acceptance model (ETAM) in a unified model of adoption, augmented by thematic analysis of user experiences. A stratified random sample of 1,297 participants—comprising 1,191 students and 105 faculty members from various departments—ensured proportional representation across the university. AHP was employed to prioritize key adoption criteria, Fuzzy DEMATEL uncovered the causal interdependencies among constructs, and ETAM validated the direct and indirect effects influencing behavioral intention. Thematic analysis provided contextual depth regarding institutional barriers and individual perceptions. Findings reveal that attitude toward GenAI and intention to use (IU) are the strongest drivers of adoption. Notably, university support (US) emerged as a central enabler, significantly influencing both awareness and perceived usefulness (PU). This study contributes a comprehensive and multi-method framework that educational institutions can use to ethically, effectively, and equitably integrate GenAI technologies into academic ecosystems.

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1. INTRODUCTION

The integration of artificial intelligence (AI) into educational contexts has drawn growing attention in recent years, prompting many academic institutions to explore the benefits of AI-driven technologies [1]. Among these innovations, ChatGPT—an advanced natural language processing (NLP) model introduced by OpenAI in 2019—stands out as a prominent example. Representing the capabilities of generative artificial intelligence (GenAI), ChatGPT employs sophisticated algorithms that produce human-like text outputs. This model leverages deep learning to generate responses that mimic natural human dialogue, enabling seamless interaction through its conversational design. ChatGPT is versatile in its functionality, offering services such as drafting essays, summarizing information, storytelling, and answering complex questions. The release of GPT-4 on March 14, 2023, marked a significant advancement in its performance and capabilities. Today, ChatGPT finds application across diverse domains, including education [2], [3], healthcare [4], and library and information services [5]. Within educational environments, it is particularly valued for its ability to deliver personalized learning support and respond to student inquiries. Furthermore, it serves as a practical tool for enhancing AI literacy, defined as the ability to understand, use, and critically assess AI systems and their broader societal impact.

Developing AI literacy involves mastering concepts, methodologies, and decision-making frameworks in AI, as well as critically evaluating these systems and their implications [6], [7]. It also encompasses understanding the legal, ethical, and societal dimensions of AI technologies and effectively engaging in discourse around these topics [8]. As an accessible and interactive platform, ChatGPT can empower both educators and learners to better navigate and participate in the evolving landscape of AI. In previous reports [9], [10], ChatGPT has been described as transformative, achieving widespread use within 6 months of its launch and setting a new record for user adoption. Its increasing popularity among university students and tech-forward industries has sparked debate: should ChatGPT be restricted as a possible enabler of academic dishonesty, or embraced for its potential to enhance learning efficiency and quality? Education has long been informed by foundational theories such as constructivism, behaviorism, situated cognition, socio-cultural theory, cognitive load theory, universal design for learning (UDL), critical race theory, social learning theory, self-efficacy theory, and self-determination theory. These frameworks, though met with varied opinions, have shaped instructional design and pedagogy over time. Similarly, the emergence of tools like ChatGPT is now subtly reshaping the teaching and learning landscape. While GenAI is still maturing, it is steadily influencing educational practice and policy. This progression raises critical questions about its broader implications. For instance, while ChatGPT does not undermine all existing learning theories, it appears to align with some—particularly self-efficacy and self-determination theory. These models suggest that learners with sufficient foundational knowledge and intrinsic motivation may benefit more from ChatGPT's immediate feedback than traditional instruction. Finally, this evolution also prompts important workforce considerations: should organizations reduce reliance on roles susceptible to automation, or instead prioritize hiring individuals who can integrate AI tools like ChatGPT to enhance productivity [11]? This study focuses on the following research questions:

- How does university support (US) influence students' and teachers' awareness, perceived ease of use (PEU), and intention to adopt GenAI tools in educational settings?
- What specific US mechanisms can be implemented to bridge the gap in awareness and effective utilization of GenAI tools among students and educators?
- How do attitudes toward GenAI and perceived usefulness (PU) influence the relationship between US and intention to use (IU) GenAI tools in education?

This study utilizes a combination of analytical hierarchy process (AHP), fuzzy decision-making trial and evaluation laboratory (Fuzzy DEMATEL), the extended technology acceptance model (ETAM), and thematic analysis to comprehensively examine the adoption of GenAI in education. Each of these methodologies brings unique strengths, allowing for a robust exploration of the factors influencing adoption. AHP is employed to prioritize critical variables such as attitude towards generative AI, IU, PU, and others. Through pairwise comparisons and the calculation of priority weights, AHP systematically identifies the most influential factors, with attitude towards generative (ATG) and IU emerging as key drivers. Additionally, the consistency ratio (CR) ensures the reliability of the pairwise judgments, adding rigor to the prioritization process.

Fuzzy DEMATEL complements AHP by analyzing causal relationships between variables, distinguishing between influential factors (e.g., PU and ATG) and those that are more influenced by others (e.g., awareness and US). Its prominence and relation scores provide critical insights into the dynamic interdependencies among variables, guiding strategic efforts to address adoption barriers. The integration of fuzzy logic in this method allows for the incorporation of subjective expert judgments, accommodating uncertainty and enhancing the practical applicability of the findings. The ETAM framework extends the traditional technology acceptance model (TAM) by incorporating additional constructs such as awareness and US. Regression and correlation analyses within ETAM reveal both direct and indirect pathways influencing user adoption. ATG is identified as the most significant predictor of IU, while indirect pathways, such as PEU influencing ATG and IU, further highlight the intricate relationships between variables. This approach provides actionable insights into how targeted interventions can effectively enhance adoption rates.

Thematic analysis is incorporated to capture qualitative dimensions of user experiences, offering a deeper understanding of the contextual factors shaping adoption, perception, and US. By identifying recurring themes and patterns in qualitative data, thematic analysis complements the quantitative methods, uncovering subjective insights into motivations, barriers, and user perceptions. This method enriches the study by highlighting factors that may not be evident in numerical analyses, such as cultural or institutional influences on adoption behavior. By integrating these methodologies, the study adopts a multi-faceted approach, combining quantitative prioritization (AHP), causal relationship mapping (Fuzzy DEMATEL), behavioral modeling (ETAM), and qualitative exploration (thematic analysis). This comprehensive framework enables a systematic understanding of GenAI adoption in education, facilitating the development of targeted strategies to address the needs of both students and educators and ensuring the equitable and effective integration of GenAI tools into educational practices.

2. LITERATURE REVIEW

2.1. Student perceptions in GenAI

Students often view GenAI as a valuable tool for academic support, recognizing its ability to enhance learning experiences and provide a competitive academic advantage [12]. Nonetheless, they remain mindful of challenges, including risks related to plagiarism, privacy issues, and the importance of establishing clear institutional guidelines [13]. In higher education, students emphasize the need for pedagogical strategies that foster critical thinking, ethical awareness, and digital literacy skills in conjunction with GenAI use [14]. Additionally, surveys reveal that many students advocate for the integration of GenAI into curricula, despite lingering concerns about its potential consequences. In addition, the opinions of individuals play a significant role in how successfully technical advancements are adopted [15]. In order to ascertain if students are prepared to incorporate technological advancements like GenAI into their teaching methods in a way that maximizes their benefits, it is crucial to consider their opinions and perceptions of these technologies [16], [17]. It is important to note that developing strategies and tactics to integrate GenAI technology into curricula and enacting suitable policies present significant obstacles for higher education institutions [18]. As a result, it is critical to engage students by learning about their perspectives and understanding their perceptions, as they are important stakeholders who actively contribute to the success of integration and development processes [19]. Teachers and administrators looking to adopt suitable and applicable policies and successfully integrate and improve procedures will get important insights from revealing university students’ perspectives on the role of GenAI in education.

2.2. Opportunities and applications

With numerous opportunities to enhance learning, GenAI technologies are increasingly being integrated into educational settings. These technologies hold the potential to boost productivity and foster student engagement by assisting educators, automating tasks, and personalizing instruction [20], [21]. In arts education, GenAI is recognized as a valuable tool for generating creative content; however, it is important to note that technology cannot replace the irreplaceable human element [22]. Similarly, in medical education, GenAI supports self-directed learning and simulates real-world scenarios, yet it also presents challenges, such as ensuring data accuracy and maintaining academic integrity [12]. Moreover, GenAI tools, such as ChatGPT, have been employed in elementary education to tailor course materials to students’ varying levels of understanding, thereby promoting motivated and effective learning [23].

2.3. The impact of GenAI on education

Through the provision of cutting-edge tools and techniques that improve learning experiences, GenAI is dramatically changing the educational landscape. Intelligent tutoring systems, adaptable learning environments, and individualized learning support are all being offered by GenAI technologies like ChatGPT, which are being incorporated into a variety of educational contexts. These technologies make it possible to create a variety of educational resources, such as texts, pictures, and videos, that are customized to the unique learning styles and profiles of each student [15], [24]. GenAI is changing learning objectives and assessment practices in higher education, encouraging career-driven competencies and lifetime learning abilities [25]. However, the incorporation of GenAI also brings up ethical issues including data privacy, academic integrity, and bias, which calls for transparent models and responsible use [26].

GenAI has an impact on specific educational areas, such as medical and engineering education, where it acts as a catalyst for change by improving teaching procedures and identifying new opportunities [27]. Notwithstanding its advantages, the quick uptake of GenAI in education necessitates rigorous evaluation of its drawbacks, including maintaining data quality and resolving ethical constraints [28]. GenAI may greatly improve student work and learning feedback, but it also needs the right kind of pedagogical assistance to help students develop their digital literacy, critical thinking, and ethical skills [14]. In order to effectively utilize GenAI promise while reducing related hazards, educators, researchers, and policymakers must work together and modify educational procedures as it develops [15].

2.4. Evolution of the extended technology acceptance model

The ETAM has proven crucial to understanding how users accept and employ technology across multiple areas. The two key constructs were the primary emphasis of Davis's original ETAM: PU and PEU. However, researchers started expanding the model to incorporate more elements that can affect consumer accept- ability as technology adoption scenarios grew increasingly intricate. For example, according to a meta-analytic analysis, the ETAM plus adds more factors to enhance model fit and consistency when forecasting technology adoption [29]. To improve the model's explanatory capacity and adapt it to various circumstances, this expansion has been essential. ETAM has been extended in several domains, including health informatics and blockchain technology. In health informatics, the model has been modified to include factors like subjective norm and self-efficacy, which represent the dynamic character of healthcare environments [30]. Similarly, to better understand adoption behaviors for blockchain technology, characteristics such as strategic management and social impact at the corporate level, as well as individual innovation and self-efficacy, have been added to the ETAM [31]. These adjustments highlight the model's adaptability and the importance of adjusting it to unique technical and organizational situations to improve forecast accuracy. The ETAM is widely used and reviewed in different sectors, including e-commerce [32], ICT in education [33], and impact recognition technology [34]. These studies have shown that the ETAM is useful for understanding user acceptability of various technological advancements. By including other relevant aspects, the ETAM gives a more thorough and context-specific knowledge of the factors impacting technology uptake and usage [35].

Additionally, ETAM has received attention in the literature and practice across most of the world. Hence, its applicability in explaining the behavior of users in the adoption of technologies is not doubtful. Studies point to several factors that could explain the acceptance of the new technology, with the extended version of TAM being widely used to test the goodness of fit of the mode [29]. The UTAUT2 model, an evolved version of TAM, has also been discussed and suggested for use in several areas, thus reflecting its development [36]. Within the context of blockchain technology adoption, an ETAM integrates both management practices and social influence as factors worth examining [31]. For instance, in the education field, TAM has been modified so that it can be applied to assess the overall effectiveness of virtual classrooms by adding new constructs such as the degree of cognitive engagement and users' well-being and comfort [28]. In the same manner, in the sharing economy, an extended TAM has also been used in the case of Airbnb with an emphasis on network effects and trust [37]. This model has also been used in predicting students' IU tablet computers based on self-efficacy and technology anxiety [38]. In the field of engineering, information and communication technology (ICT) teaching methods have somehow been reviewed to extend the TAM to evaluate the level of engagement and learning of students [39]. For purposes of augmented reality (AR) and virtual reality (VR) in education, a modified TAM looks at teachers, the learning TAM of WeChat has been expanded to incorporate behavioral constructs such as conforming behavior and language self-esteem, which are helpful for language learners [40]. Preparedness by adding technological content knowledge [41]. Finally, the adoption of mobile food ordering applications has also been examined using the extended [42] but rather concentrating on personal self-efficacy and trustworthiness. It can be seen from the previous studies that the ETAM is extensible in context and psychological parameters for a better understanding of the acceptance of various technologies by the users.

3. METHOD

3.1. Data collection

An online survey was administered via a Google Form link and distributed through various social media platforms from October 23 to December 9, 2024. To enhance representativeness, random sampling was employed by inviting participants across different campuses and departments of Cebu Technological University, ensuring a diverse demographic of both faculty and students. This method was chosen for its efficiency, convenience, and cost-effectiveness. A total of 1,418 responses were collected; however, 122 were identified as duplicates. After data cleaning, 1,296 valid responses remained and were included in the final analysis. There were more female (66%) than male (34%) participants. Their ages ranged from 17 to 61 years old, with 90% clustered around the age range of 17 to 24 years. Additionally, 92% of the participants were students, while the remaining 8% were faculty members.

3.2. Measurement

The main instrument used in the study was a survey questionnaire which included measurement items that were adapted from validated scales. The constructs examined were: US with 8 items, awareness with 4 items, PU with 5 items, PEU with 4 items, ATG AI with 4 items, and IU with 4 items. All measurement items were rated on a 7-point Likert scale, ranging from "strongly agree" to "strongly disagree". Meanwhile, actual usage (AU) was measured using a scale of 1 to 7 with 1 as "never" and 7 as "every time". For the qualitative component, respondents answered 3 open-ended questions regarding their university's policies on GenAI, as well as the benefits and challenges they experienced in using it. The survey was administered via Google Forms for convenient access.

3.3. Construct and definition

The instrument used in this study was based on the constructs discussed in sub-sections. The respondents of the study are students and faculty from Cebu Technological University. The item indicators in the following sections were adapted and reworded from previously validated instruments to align with the specific context of this study on GenAI in higher education. Original sources have been appropriately cited within each corresponding section.

3.4. Actual usage

AU refers to real behavior in adopting a system. It is measured by the amount of time spent interacting with the technology or the frequency of use. Item indicators: how frequently do you use GenAI in your teaching, research, or administrative responsibilities? i) I have never used it; ii) I use it less than 10% of the time; iii) I use it around 30% of the time; iv) I use it approximately half of the time; v) I use it in about 70% of my tasks; vi) I use it in nearly all tasks (around 90%); and vii) I rely on it every time.

3.5. Intention to use

IU refers to the user's intention or willingness to use technology [43]. Item indicators: i) I am open to using GenAI tools like ChatGPT moving forward; ii) If access to GenAI is available, I would plan to use it [44]; iii) I expect to keep using GenAI tools in my work; and iv) I would suggest that others try using GenAI [45].

3.6. Attitude toward GenAI

The degree of students' favorable or unfavorable evaluation regarding adopting GenAI technologies in their learning process [46]. Item indicators: i) I believe the use of GenAI is beneficial; ii) I am at ease incorporating GenAI into my activities; iii) I am pleased with my experience using GenAI [47]; and iv) I am supportive of initiatives to use GenAI.

3.7. Perceived usefulness

The extent to which a person thinks a specific system would improve performance at work [38]. Item indicators: i) GenAI can help improve the quality of my outputs [48]; ii) Using AI tools makes me more productive; iii) My efficiency in tasks increases when I use GenAI; iv) GenAI can reduce the time I spend on routine work; and v) I believe GenAI contributes positively to teaching and learning processes [49].

3.8. Perceived ease of use

The extent to which a person thinks that utilizing a specific method would be easy. Item indicators: i) I think I can quickly grasp how to use GenAI tools; ii) It does not take much effort to work with GenAI; iii) I consider GenAI user-friendly; and iv) I find it easy to learn how to use GenAI tools effectively.

3.9. University support

It refers to the relevant supporting policies for the use of GenAI. Item indicators: i) The university offers support or initiatives for GenAI use; ii) I value institutional resources related to GenAI; iii) My university promotes innovation through the use of emerging technologies like GenAI; iv) There are opportunities for training and development in using GenAI; v) The institution has clear policies on when AI use is appropriate; vi) Guidelines are available to ensure academic honesty when using GenAI; vii) Responsible use of GenAI is addressed by the institution's strategy; and viii) The university has ways to monitor and manage inappropriate AI usage.

3.10. Awareness

It encompasses understanding of the capabilities, applications, and limitations of GenAI [50]. Item indicators: i) I am familiar with what GenAI is; ii) I talk about GenAI with colleagues or peers; iii) I understand how to use GenAI appropriately; and iv) I recognize how GenAI may affect or influence my professional work.

3.11. Sample size, validity, and control measures

The study analyzed a total of 1,296 valid responses after data cleaning, which exceeds the recommended minimum threshold for structural equation modeling (SEM). SEM literature advises that a sample size of at least 200 respondents or a participant-to-parameter ratio of 10:1 is required to ensure reliable and generalizable results [51], [52]. With this large and diverse sample, the study achieved sufficient statistical power and minimized sampling bias. To ensure content validity, all constructs in the questionnaire were adapted from previously validated scales, and reviewed by domain experts in educational technology and survey design. Prior to full deployment, a pilot test was conducted with 30 participants to identify ambiguities and enhance clarity. Construct validity was further established through confirmatory factor analysis during data processing [53]. Instrument reliability was evaluated using Cronbach's alpha, and all constructs demonstrated strong internal consistency, with alpha values exceeding the commonly accepted threshold of 0.70 [54]. This indicates that the item groupings within each construct reliably measure the same underlying concepts. Confounding variables were addressed through stratified random sampling across various colleges, departments, and roles (students and faculty) of Cebu Technological University. This strategy ensured the representativeness of subgroups. Additionally, duplicate entries (n=122) were removed to prevent redundancy and reduce bias. During the analysis stage, statistical control techniques were employed to account for the effects of demographic variables such as age, gender, and university role, thereby isolating the effects of the core constructs on user behavior and intentions.

3.12. Descriptive analysis

Table 1 summarizes the average ratings for students and teachers across key variables. The table highlights descriptive statistics of the average ratings for students and teachers. Students and teachers perceive and use GenAI differently. For example, teachers rated PU and IU higher than students, suggesting a stronger inclination toward integrating GenAI into their activities. Variables like awareness and US show lower ratings among students, indicating potential gaps in institutional guidance. Institutions may need to focus on increasing awareness and providing better support for students to ensure equitable access and effective use of GenAI tools.

Table 1. Descriptive statistics of key variables

Variable	Students	Teachers
AU	3.93	3.88
PU	5.15	5.84
ATG	4.80	5.67
IU	4.93	6.06
PEU	4.50	5.20
US	4.30	5.10
Awareness	3.70	4.50

3.13. T-Test analysis

Table 2 shows the results of the T-tests comparing students and teachers. The table presents statistically significant differences in their perceptions and usage of GenAI across nearly all variables. Notably, teachers exhibit a significantly higher IU than students, with a p-value of less than 0.001. Additionally, students demonstrate significantly lower levels of awareness regarding GenAI. These findings underscore the need for targeted training and workshops designed specifically for students to bridge these gaps. Given their more favorable perceptions, educators are well-positioned to serve as facilitators, supporting students in the effective adoption and integration of GenAI tools.

Table 2. T-Test results comparing students and teachers

Variable	t-statistic	p-value
AU	0.39	0.70
IU	-7.15	8.0×10^{-11}
ATG	-8.56	3.6×10^{-14}
PU	-6.25	1.2×10^{-9}
PEU	-5.20	5.1×10^{-8}
US	-4.30	1.0×10^{-5}
Awareness	-3.70	1.5×10^{-4}

3.14. Analytical hierarchy process

3.14.1. Mathematical formulation of AHP

The AHP involves the following steps: construct the pairwise comparison matrix A, where a_{ij} represents the relative importance of criteria i over j.

– Normalize the matrix:

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{1}$$

– Compute the priority weights:

$$w_i = \frac{\sum_{j=1}^{n} n_{ij}}{n} \tag{2}$$

– Calculate the consistency index (CI):

$$\lambda_{max} = \frac{\sum_{i=1}^{n} (A \cdot w)_i / w_i}{n} \tag{3}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{4}$$

– Calculate the CR:

$$CR = \frac{CI}{RI} \tag{5}$$

where RI is the random index for a given n. The AHP methodology ensures consistency by checking the value of the CR. If CR<0.1, the pairwise comparisons are consistent and acceptable. If CR≥0.1, the pairwise comparison matrix needs revision.

3.14.2. Priority weights

The priority weights for all variables, calculated using the AHP method, are shown in Table 3. The table outlines the AHP priority weights, identifying ATG AI and IU as the most critical factors influencing adoption, as they received the highest priority weights. In contrast, variables such as awareness and US were assigned lower weights, suggesting they play a secondary role compared to attitude and intention. These results highlight the importance of fostering a positive attitude toward GenAI to encourage broader adoption. The priority weights for the seven criteria recognized as affecting the adoption and utilization of GenAI were obtained through the AHP. These weights reflect the relative significance of each factor as seen by the respondents. The findings indicate that the ATG AI carries the greatest weight (0.25), implying that users' overall favorable or unfavorable assessment of GenAI is the key factor influencing its adoption. Next is IU with a weight of 0.20, along with PU at 0.18, showing that the drive to keep using the technology and the belief in its advantages are significant influences as well. At the same time, AU carries a moderate weight of 0.15, indicating that present behavior holds significance but is less impactful than the attitudinal and intention-driven factors. PEU (0.10), US (0.07), and awareness (0.05) are rated lower, indicating that while these elements influence the overall choice, they are not the main factors from the users' viewpoint.

Table 3. AHP priority weights

Criteria	Priority weights
AU	0.15
IU	0.20
ATG	0.25
PU	0.18
PEU	0.10
US	0.07
Awareness	0.05

3.15. Fuzzy DEMATEL Analysis

3.15.1. Mathematical formulation of Fuzzy DEMATEL

The Fuzzy DEMATEL method involves the following steps: construct the direct-relation matrix F, where f_{ij} represents the direct influence of factor i on factor j.

– Normalize the direct-relation matrix:

$$N_{ij} = \frac{f_{ij}}{max\left(\sum_{j=1}^{n} f_{ij}\right)} \tag{6}$$

– Normalize the direct-relation matrix:

$$T = N(I - N)^{-1} \tag{7}$$

where *T* is the total influence matrix, *I* is the identity matrix, and *N* is the normalize direct-relation matrix.
– Calculate the prominence *(D+R)* and relation *(D−R)* for each factor:
Total influence given

$$D_i = \sum_{j=1}^{n} t_{ij} \tag{8}$$

Total influence received

$$R_i = \sum_{i=1}^{n} t_{ij} \tag{9}$$

$$D + R = Prominence\ (Sum\ of\ Given\ and\ Received\ Influences) \tag{10}$$

$$D + R = Prominence\ (Sum\ of\ Given\ and\ Received\ Influences) \tag{11}$$

– Interpret the results: i) factors with high D+R are prominent and play an important role in the system; ii) factors with positive D−R are net influencers (causing more effect than they receive); and iii) factors with negative D−R are net receivers (receiving more effect than they cause).

3.15.2. Results

The Fuzzy DEMATEL results, including prominence (D+R) and relation (D-R) for all variables, are presented in Table 4. The table presents the results of the Fuzzy DEMATEL analysis, highlighting PU and ATG AI as the primary driving factors within the system, both exhibiting high prominence scores. In contrast, awareness and US are more reactive variables, meaning they are more influenced by other factors than they influence others themselves. These insights suggest that institutions aiming to increase GenAI adoption should focus on enhancing the PU of these tools—such as by demonstrating practical, real-world applications—which can, in turn, positively shape user attitudes and drive further adoption. Furthermore, the PU surfaced as the most significant factor, holding the highest prominence score (D+R=24). This suggests that PU is closely linked with other variables in the system; nonetheless, its negative relation value (D−R=-2) indicates it is mainly affected by other factors instead of being a key driver itself. In the same way, IU demonstrates a significant interaction level (D+R=22) yet has a slightly negative relation value (D−R=-1), suggesting it also serves as more of an outcome variable within the system.

Conversely, AU shows substantial interaction (D+R=21) and a beneficial causal link (D−R=+4), marking it as a key factor that directly influences behaviors in the model. ATG AI has a significant causal impact (D−R=+3), indicating that a favorable attitude facilitates and enhances the acceptance and effect of other elements. Significantly, PEU emerges as the most influential causal element, boasting the highest positive correlation score (D−R=+5), signifying it is the main catalyst that affects other variables throughout the system. At the same time, US exhibits diminished overall significance (D+R=18) and a negative relationship value (D−R=-3), suggesting it operates more as a responsive element influenced by external factors rather than instigating change. Finally, awareness has the least significance (D+R=17) and a neutral relationship value (D−R=0), indicating that it maintains a balanced position—neither strongly influencing nor being greatly influenced—thus serving as a potential stabilizer in the model.

Table 4. Fuzzy DEMATEL results including all variables

Criteria	Prominence (D+R)	Relation (D-R)
AU	21	4
IU	22	-1
ATG	20	3
PU	24	-2
PEU	19	5
US	18	-3
Awareness	17	0

3.16. Extended technology acceptance model

The ETAM framework includes the constructs shown in Table 5, with their correlations. The table shows correlation matrix of key constructs from the ETAM, highlighting strong relationships that influence

GenAI adoption in education. The strongest correlation is between ATG AI and IU (r=0.82), emphasizing attitude as a key driver of adoption. PU also strongly correlates with both ATG (r=0.78) and IU (r=0.75), while PEU significantly relates to PU, ATG, and IU. US and awareness show moderate but meaningful correlations, indicating their indirect role. These findings reinforce the importance of enhancing attitudes, usefulness, and ease of use, supported by institutional strategies.

Table 5. Correlation matrix for ETAM constructs

Construct	US	Awareness	PU	PEU	ATG	IU
US	1.00	0.48	0.51	0.57	0.53	0.51
Awareness	0.48	1.00	0.51	0.52	0.49	0.50
PU	0.51	0.51	1.00	0.68	0.78	0.75
PEU	0.57	0.52	0.68	1.00	0.63	0.62
ATG	0.53	0.49	0.78	0.63	1.00	0.82

3.16.1. Regression analysis results

Table 6 presents the regression results for the ETAM, showing that ATG AI is the strongest predictor of IU (β=0.510), followed by PU (β=0.222). PEU had a smaller effect (β=0.081), while awareness and US showed minimal direct influence. These results highlight the importance of fostering positive attitudes and PU to drive adoption, supported by targeted awareness and institutional strategies.

3.16.2. Indirect effects

ATG AI has the strongest direct impact on IU (regression coefficient=0.510). Indirect pathways (PEU→attitude→IU) also contribute to user acceptance. US has a weaker direct effect, but it indirectly influences adoption via other factors like PU. Efforts to improve the ease of use and ATG AI will have the most significant impact on adoption rates. Universities should provide targeted support programs to enhance ease of use and foster positive attitudes. Table 7 presents the computed path effects among the variables, showing how PU, PEU, and US influence AI adoption intention (IU) through attitude toward GenAI.

3.16.3. Thematic analysis

Table 8 shows emergent themes or narratives when we ask the respondents on the question: "what policies does your school have regarding the use of GenAI in education?" Table 8 presents emergent themes from the thematic analysis of school policies related to the use of GenAI in education, offering important qualitative insights that complement the quantitative data. The thematic analysis provides valuable qualitative insights into the adoption of GenAI in education, complementing broader quantitative findings often observed in related research. The identified themes reveal gaps in institutional support and highlight the diverse attitudes and practices surrounding GenAI integration in schools. The absence of a unified school-wide policy, as noted in the thematic analysis, reflects a lack of structured awareness initiatives and institutional guidance. This gap likely contributes to limited understanding and inconsistent practices, particularly among students, who often rely on fragmented or instructor-specific rules. Without clear policies or dissemination mechanisms, the potential benefits of GenAI tools may remain underutilized, underscoring the need for comprehensive institutional strategies.

The variability in instructor responses, highlighted in the analysis, underscores the role of teachers in shaping the adoption of GenAI. Instructors' differing levels of familiarity, attitudes, and willingness to integrate these tools result in inconsistent student experiences. This disparity suggests that while some educators view GenAI as a valuable tool, others remain hesitant, emphasizing the need for standardized training and institutional support to bridge these gaps.

Ethical considerations also emerge as a key theme, with schools emphasizing the importance of academic integrity and responsible use of AI. This focus aligns with the broader recognition that fostering positive attitudes toward technology depends on addressing ethical concerns. Clear guidelines on the ethical use of AI, paired with transparency and proper citation practices, are critical for ensuring responsible adoption. Additionally, the themes of training, guidance, and balancing benefits with risks highlight the importance of institutional efforts in promoting effective adoption. Providing resources, training, and real-world applications can enhance the PU of AI tools while mitigating risks such as over-reliance or misuse. By fostering a positive attitude through targeted interventions and success stories, institutions can help both students and educators view GenAI as a tool that enhances, rather than replaces, traditional learning processes. Overall, the thematic analysis offers actionable insights for institutions seeking to integrate GenAI effectively. Addressing the gaps in awareness, institutional support, and training while emphasizing ethical use can create an environment where GenAI tools are adopted equitably and effectively.

Table 6. ETAM regression coefficients

Construct	Coefficient
Intercept	-0.107
US	0.034
Awareness	0.065
PU	0.222
PEU	0.081
ATG	0.510

Table 7. Path effects of variables on AI adoption intention

Path	Effect
PU→ATG→IU	0.113
PEU→ATG→IU	0.041
US→PU→IU	0.007

Table 8. Emergent themes on school policies regarding the use of GenAI in education

Emergent themes	Subthemes	Excerpts from the questionnaire
Unclear institutional policies on GenAI	Lack of awareness or formal policies Varied instructor responses	There are no specific rules about AI in our school, but we are encouraged not to use it. I don't know the policies in school. I don't think our school has specific policies on GenAI. I haven't seen a full or comprehensive written policy regarding the use of GenAI yet. If there are policies, they must be known only to select individuals. I have not seen a written policy, maybe there is, but not disseminated to all employees. Some teachers allow us to use AI, provided it is used properly, while others do not permit students to use it. It is the teacher that imposes policies in his/her class regarding the use of AI. Some teachers support AI while others don't. The policies regarding GenAI in education vary depending on the teacher or the course.
Emphasizing ethical and responsible use	Responsible usage through ethical use and academic integrity	Schools are emphasizing the ethical use of AI, including avoiding plagiarism and ensuring that AI-generated content is properly cited. The school emphasized the importance of original work and restricted the use of AI to ensure that we submit our own ideas and writings. GenAI should not be used to engage in plagiarism, cheating, or any form of dishonesty in academic work. Students must disclose any use of AI tools in their work to maintain transparency and originality. The school teaches us how to use GenAI in a way that helps us to understand and generate ideas but ensures we are aware of the implications of using it.
	Prohibition or restrictions	Students might be allowed to use GenAI for brainstorming but are required to refine and personalize their work.
Promoting awareness and adaptability	Training and guidance A and data privacy	Providing students and faculty with training to use AI tools effectively and responsibly, emphasizing their role as supplementary aids rather than replacements for learning. The school provides resources and training for teachers and students to understand how to use AI responsibly and effectively. The school promotes the integration of AI into education while ensuring proper guidance on how to use it. Our policies ensure compliance with privacy and security regulations, especially when using AI for academic purposes. The school emphasizes that AI-generated content must comply with data privacy policies to protect student and institutional information. The school has emphasized responsible data handling when engaging with AI tools, to mitigate risks associated with privacy breaches.
	Balancing benefits and risks	Don't use AI all the time because some information is not correct. The misuse and abuse of AI can lead to laziness in education. Using AI too much might cause students to depend on it entirely and lose their ability to think independently. GenAI is helpful but must be balanced with independent thought and effort. The school emphasizes that AI should be a learning tool rather than a shortcut for academic tasks.

4. CONCLUSION

This study highlights the pivotal role of US in facilitating the adoption of GenAI tools among students and educators. Clear differences in perceptions and usage emerged: teachers reported higher levels of IU (6.06) and PU (5.84) compared to students (IU=4.93, PU=5.15). Moreover, students demonstrated lower awareness (3.70) and perceived US (US=4.30), identifying critical areas for institutional improvement. Quantitative results confirmed that ATG AI was the most influential predictor of IU (coefficient=0.510), with PU and PEU playing significant roles in shaping both attitudes and adoption behavior.

The study also identified an indirect effect—PEU→attitude→IU (effect=0.041)—which underscores the complex, interconnected nature of adoption factors. Thematic analysis from qualitative data revealed key institutional-level barriers, such as the absence of unified school-wide policies and inconsistencies in how instructors implement AI tools. Ethical concerns were also prominent, with participants emphasizing issues related to academic integrity, originality, and data privacy. These findings point to a need for structured training programs, clear policy guidance, and the responsible, sustainable integration of AI technologies into educational settings.

However, the study has its limitations. The use of a cross-sectional methodology restricts the ability to establish causal relationships, and the sample, drawn from a single university, may limit the generalizability of the findings. Self-reported responses could also be influenced by social desirability or memory bias. Future research should consider longitudinal approaches to observe how adoption changes over time—especially following policy implementations or support initiatives. Broader samples from multiple institutions and disciplines would offer a more comprehensive perspective. Moreover, examining the impact of GenAI on learning outcomes, ethical decision-making, and field-specific applications can provide deeper insight into its evolving role in education.

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AUTHOR CONTRIBUTIONS

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Google Sheets at the following link: https://docs.google.com/spreadsheets/d/1_tqhrw2Bu0tRyef-qjRE75lHRbqezV_L.

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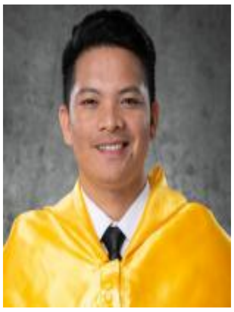

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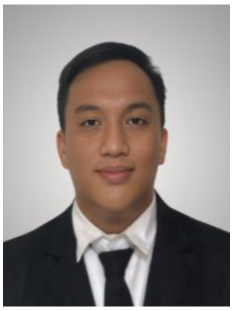

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