# AI LANGUAGE PLATFORM ADOPTION AMONG INDUSTRIAL TECHNOLOGY STUDENTS: AN EXTENDED TECHNOLOGY ACCEPTANCE MODEL USING PLS-SEM

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***ABSTRACT*** *Generative artificial intelligence (GenAI) has become an important educational technology that supports learning, academic writing, problem-solving, and self-directed study. Although **TAM** is widely used to explain technology adoption, it may not fully capture the unique characteristics of GenAI, particularly users' perceptions of the reliability of AI-generated information. This study extends TAM by incorporating **Perceived Reliability** as an additional determinant of students' **Behavioral Intention** to adopt AI language platforms. A quantitative cross-sectional survey was conducted among **335 Bachelor of Science in Industrial Technology students** at a Philippine state university, and the data were analyzed using **PLS-SEM**. Results showed that **Perceived Ease of Use** significantly influenced **Perceived Usefulness** and **Behavioral Intention**, while **Perceived Usefulness** and **Perceived Reliability** positively affected **Behavioral Intention**. Behavioral Intention was the strongest predictor of **Actual Usage Frequency**. **PLS-Predict** confirmed satisfactory predictive performance, while **IPMA** identified Perceived Reliability as a priority for institutional improvement. The findings extend TAM by highlighting the importance of information reliability in GenAI adoption and provide practical guidance for universities to promote responsible AI integration through AI literacy, information verification, and institutional policy.*

**Keywords:** Artificial Intelligence; Technology Acceptance Model; Perceived Reliability; Generative AI; Industrial Technology; PLS-SEM

## INTRODUCTION

Generative artificial intelligence (GenAI) has rapidly transformed higher education by changing how students access information, solve problems, and engage in academic learning. Powered by large language models (LLMs), AI language platforms such as ChatGPT, Google Gemini, Microsoft Copilot, and Claude provide conversational assistance for academic writing, programming, brainstorming, concept clarification, and self-directed learning. Unlike conventional search engines that retrieve existing information, these platforms generate context-specific responses that support personalized learning and immediate academic assistance **[1–4]**. Consequently, GenAI has become an increasingly important educational technology, offering new opportunities to enhance teaching, learning, and student engagement.

Recent studies have reported that AI language platforms improve learning efficiency, promote independent learning, and enhance students' understanding of complex concepts through personalized feedback and interactive support **[1,5,6]**. In response, higher education institutions are increasingly integrating AI-enabled tools into teaching, assessment, and curriculum delivery to prepare graduates for an AI-driven society **[7,8]**. These developments indicate that GenAI is becoming an integral component of contemporary higher education rather than simply an emerging educational technology.

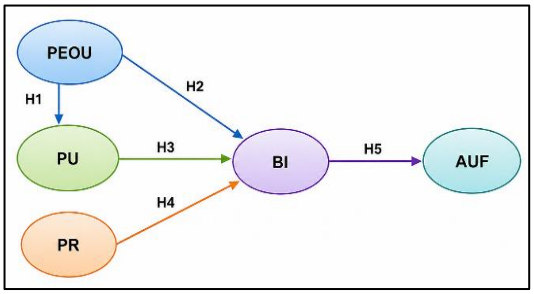
Despite these advantages, the rapid adoption of GenAI has also raised significant pedagogical and ethical concerns. AI language platforms may generate inaccurate information, fabricated references, biased responses, or misleading content that requires careful verification before academic use **[9–11]**. Such limitations have heightened concerns regarding academic integrity, students' overreliance on AI, and declining critical thinking skills **[12,6]**. As a result, universities have begun implementing AI governance policies and AI literacy initiatives that promote ethical use, transparency, and critical evaluation of AI-generated information.

Understanding the factors influencing students' adoption of GenAI has therefore become an important research priority. Among the most widely used frameworks for explaining technology adoption is TAM **[13]**, which posits that **Perceived Ease of Use (PEOU)** and **Perceived Usefulness (PU)** shape users' **Behavioral Intention (BI)** and subsequent technology use. Owing to its strong explanatory capability, TAM has been extensively applied to studies involving educational technologies, including AI language platforms **[14–17]**.

However, the emergence of GenAI presents characteristics that extend beyond the assumptions of traditional TAM. Unlike conventional technologies that primarily retrieve existing information, AI language platforms generate original content whose accuracy, consistency, and credibility may vary. Consequently, students evaluate not only whether these technologies are useful and easy to use but also whether AI-generated information is sufficiently reliable for academic purposes. Recent studies have therefore suggested extending technology acceptance models by incorporating constructs related to trust, information quality, and reliability **[18–20]**. Among these, Perceived Reliability remains relatively underexplored despite its potential importance in explaining students' adoption of generative AI.

This issue is particularly relevant in Industrial Technology education, where students engage with engineering concepts, laboratory activities, manufacturing systems, and technical procedures that require accurate and dependable information. Inaccurate AI-generated responses may adversely affect technical learning and professional decision-making. Nevertheless, empirical studies examining GenAI adoption among Industrial Technology students remain limited, particularly in Philippine higher education. Moreover, few studies have explicitly examined the role of Perceived Reliability within TAM in explaining students' intention to adopt AI language platforms **[4,20,21]**.

To address these gaps, this study extends TAM by incorporating Perceived Reliability as an additional determinant of Behavioral Intention. Using PLS-SEM, the study examines the relationships among Perceived Ease of Use, Perceived Usefulness, Perceived Reliability, Behavioral Intention, and Actual Usage Frequency among Bachelor of Science in Industrial Technology students. By integrating information reliability into TAM, this study contributes to the growing literature on generative AI adoption and provides evidence-based insights for AI literacy initiatives, curriculum development, and institutional policies supporting the responsible integration of GenAI in higher education.




**roposed Extended Technology Acceptance Model**

## 2. Methodology

### 2.1 Research Design

This study employed a quantitative, cross-sectional research design to examine the determinants of generative AI language platform adoption among undergraduate students using an Extended Technology Acceptance Model (TAM). The proposed model extends the original TAM by incorporating Perceived Reliability (PR) as an additional predictor of Behavioral Intention (BI). Specifically, the model investigates the direct effects of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU) and Behavioral Intention, as well as the effects of Perceived Usefulness and Perceived Reliability on Behavioral Intention, which subsequently predicts Actual Usage Frequency (AUF).

Given the study's objective of testing and extending an established theoretical framework while simultaneously assessing its predictive capability, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. Compared with covariance-based SEM, PLS-SEM is particularly appropriate for prediction-oriented research, theory development, and the analysis of complex causal relationships among latent constructs. It has become one of the most widely adopted analytical approaches in educational technology and information systems research, particularly in studies examining technology acceptance and behavioral intention **[22,23]**.

### 2.2 Participants and Sampling

### 2.2 Participants

The study was conducted at a Philippine state university involving Bachelor of Science in Industrial Technology (BSIT) students who had prior experience using at least one AI language platform, including ChatGPT, Google Gemini, Microsoft Copilot, or Claude, for academic purposes. Industrial Technology students were selected because their academic programs require frequent engagement with engineering concepts, laboratory activities, manufacturing systems, and technical problem-solving, where the accuracy and reliability of information are essential for effective learning.

A total of 335 undergraduate students participated in the study. The sample size was considered adequate for PLS-SEM analysis and exceeded the minimum sample requirements recommended for structural equation modeling involving multiple latent constructs **[21]**. Respondents were selected using a structured survey procedure to ensure that participants possessed sufficient experience with AI language platforms to evaluate the constructs investigated in the study.

### 2.3 Research Instrument

Data were collected using a structured self-administered questionnaire comprising five latent constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Perceived Reliability (PR), Behavioral Intention (BI), and Actual Usage Frequency (AUF). Measurement items were adapted from established TAM studies and recent literature on generative AI adoption, with modifications to suit the educational context of AI language platforms. Perceptual constructs were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), while AUF was assessed through indicators reflecting students' frequency of AI language platform use for academic purposes. The instrument underwent content validation to ensure the clarity, relevance, and appropriateness of all measurement items.

### 2.4 Data Collection Procedure

Data were collected during the regular academic semester following institutional approval. Participation was voluntary, and respondents were informed of the study's purpose before completing the questionnaire. Ethical principles of informed consent, anonymity, confidentiality, and voluntary participation were strictly observed. No personally identifiable information was collected, and respondents were free to withdraw from the study at any stage without penalty.

### 2.5 Data Analysis

Data were analyzed using SmartPLS 4 following the two-stage PLS-SEM procedure recommended by Hair et al. **[21]**. The measurement model was evaluated through indicator reliability, internal consistency reliability (Cronbach's alpha, composite reliability, and rho_A), convergent validity (Average Variance Extracted [AVE]), and discriminant validity using the Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait Ratio (HTMT). The structural model was then assessed using Variance Inflation Factor (VIF), bootstrapping with 5,000 resamples, path coefficients (β), t-values, p-values, coefficients of determination ($R^2$), and predictive relevance ($Q^2$). To assess predictive capability and practical significance, PLS-Predict and Importance–Performance Map Analysis (IPMA) were also performed.

### 3.1 Measurement Model Assessment

The measurement model demonstrated satisfactory reliability and validity. All indicator loadings exceeded the recommended threshold (0.748–0.911). Internal consistency was confirmed, with Cronbach's alpha, composite reliability, and rho_A values above 0.70, while AVE values (0.697–0.772) exceeded the recommended 0.50 threshold, indicating convergent validity. Discriminant validity was established using the Fornell–Larcker criterion, HTMT, and cross-loading analysis, confirming that the constructs were empirically distinct and suitable for structural model evaluation.

**Table 1** presents the reliability and convergent validity statistics for all latent constructs.

**Table 1. Reliability and Convergent Validity of the Measurement Model**

| Construct | Cronbach's α | Composite Reliability | AVE |
|---|---|---|---|
| Perceived Ease of Use | 0.906 | 0.930 | 0.726 |
| Perceived Usefulness | 0.918 | 0.938 | 0.752 |
| Perceived Reliability | 0.892 | 0.920 | 0.697 |
| Behavioral Intention | 0.901 | 0.931 | 0.772 |
| Actual Usage Frequency | 0.884 | 0.920 | 0.742 |

### 3.2 Structural Model Assessment

Following validation of the measurement model, the hypothesized relationships were examined using the structural model. Prior to hypothesis testing, collinearity diagnostics indicated that all **Variance Inflation Factor (VIF)** values were below the recommended threshold, confirming the absence of multicollinearity among the predictor constructs.

Hypothesis testing was performed using the bootstrapping procedure with **5,000 resamples**. As summarized in **Table 2**, all hypothesized relationships were statistically significant (**$p < .001$**), providing empirical support for the proposed Extended Technology Acceptance Model.

Consistent with the original assumptions of TAM, **Perceived Ease of Use** exerted a strong positive effect on **Perceived Usefulness** ($\beta = 0.689$, $t = 18.924$, $p < .001$), indicating that students who perceive AI language platforms as easy to use are more likely to recognize their educational value. Perceived Ease of Use also directly influenced **Behavioral Intention** ($\beta = 0.243$, $t = 4.918$, $p < .001$), suggesting that usability remains an important determinant of students' willingness to adopt AI language platforms.

Among the antecedents of Behavioral Intention, **Perceived Usefulness** emerged as the strongest predictor ($\beta = 0.418$, $t = 8.274$, $p < .001$), demonstrating that students primarily adopt AI language platforms because they perceive them as beneficial for improving learning and academic performance. More importantly, **Perceived Reliability** also exerted a significant positive influence on Behavioral Intention ($\beta = 0.311$, $t = 6.127$, $p < .001$), confirming that students' confidence in the accuracy and dependability of AI-generated information constitutes an important determinant of technology acceptance.

Finally, **Behavioral Intention** exhibited a substantial positive effect on **Actual Usage Frequency** ($\beta = 0.776$, $t = 24.816$, $p < .001$), indicating that students' intentions to use AI language platforms translate into consistent academic utilization.

The explanatory capability of the model was likewise satisfactory. The proposed model explained **47.5%** of the variance in **Perceived Usefulness**, **68.9%** of the variance in **Behavioral Intention**, and **60.2%** of the variance in **Actual Usage Frequency**. Moreover, all endogenous constructs produced positive **Stone–Geisser's $Q^2$** values, indicating acceptable predictive relevance.

**Table 2. Structural Model Results**

| Hypothesis | Structural Path | β | *t* | *p* | Decision |
|---|---|---|---|---|---|
| H1 | PEOU → PU | 0.689 | 18.924 | < .001 | Supported |
| H2 | PEOU → BI | 0.243 | 4.918 | < .001 | Supported |
| H3 | PU → BI | 0.418 | 8.274 | < .001 | Supported |
| H4 | PR → BI | 0.311 | 6.127 | < .001 | Supported |
| H5 | BI → AUF | 0.776 | 24.816 | < .001 | Supported |

### 3.3 Predictive Performance of the Extended TAM

To complement the explanatory assessment, the predictive performance of the proposed model was evaluated using **PLS-Predict** and **Importance–Performance Map Analysis (IPMA)**. These complementary analyses provide additional evidence regarding the model's practical utility beyond conventional hypothesis testing.

The **PLS-Predict** results indicated that the proposed PLS model consistently produced lower **Root Mean Squared Error (RMSE)** values than the corresponding linear regression benchmark across all endogenous constructs. This finding demonstrates satisfactory out-of-sample predictive performance and indicates that the Extended Technology Acceptance Model possesses not only explanatory capability but also meaningful predictive accuracy for future observations.

The coefficient of determination (**$R^2$**) and predictive relevance (**$Q^2$**) further confirmed the robustness of the proposed model. Behavioral Intention achieved the highest explanatory power (**$R^2 = 0.689$**), followed by Actual Usage Frequency (**$R^2 = 0.602$**) and Perceived Usefulness (**$R^2 = 0.475$**). Positive **$Q^2$** values for all endogenous constructs likewise indicate that the model has acceptable predictive relevance.

**Table 3. Predictive Accuracy of the Structural Model**

| Construct | $R^2$ | $Q^2$ |
|---|---|---|
| Perceived Usefulness | 0.475 | 0.328 |
| Behavioral Intention | 0.689 | 0.497 |
| Actual Usage Frequency | 0.602 | 0.431 |

The **Importance–Performance Map Analysis (IPMA)** provided additional managerial insights by identifying constructs with the greatest potential for improvement. While **Perceived Usefulness** demonstrated the highest importance in predicting Behavioral Intention, **Perceived Reliability** exhibited comparatively lower performance despite its substantial importance. This finding suggests that improving students' confidence in the accuracy, consistency, and dependability of AI-generated information may yield greater improvements in AI adoption than further enhancements in system usability alone.

Accordingly, higher education institutions should prioritize initiatives that strengthen AI literacy, critical evaluation of AI-generated content, source verification, and responsible AI use. Such interventions are likely to increase students' confidence in generative AI and facilitate its effective integration into academic learning.

**Table 4. Summary of PLS-Predict and IPMA Results**

| Construct | PLS-Predict | IPMA Interpretation |
|---|---|---|
| Perceived Usefulness | Lower RMSE than linear model | Highest importance |
| Perceived Reliability | Lower RMSE than linear model | High importance; improvement priority |
| Actual Usage Frequency | Lower RMSE than linear model | Good predictive capability |

## 4. DISCUSSION

The present study investigated the determinants of generative AI language platform adoption among Industrial Technology students by extending the Technology Acceptance Model (TAM) with Perceived Reliability. Consistent with the proposed theoretical framework, all hypothesized relationships were statistically significant, indicating that students' adoption of AI language platforms is jointly influenced by perceptions of usability, usefulness, and the reliability of AI-generated information. Overall, the findings support the applicability of the Extended Technology Acceptance Model in explaining students' behavioral intentions and actual usage of generative AI within higher education.

### 4.1 Perceived Ease of Use as a Driver of Perceived Usefulness

The results demonstrated that Perceived Ease of Use (PEOU) exerted a strong positive influence on Perceived Usefulness (PU), indicating that students who perceive AI language platforms as simple and effortless to operate are more likely to recognize their educational value. This finding is consistent with the original Technology Acceptance Model proposed by Davis **[12]**, which posits that technologies requiring minimal effort are perceived as more useful because users can accomplish their tasks more efficiently.

The finding also aligns with recent investigations on generative AI adoption in higher education **[13–15]**, which consistently report that intuitive interfaces and user-friendly interactions enhance students' perceptions of AI-assisted learning. AI language platforms employ conversational interfaces that allow students to communicate using natural language instead of complex commands, thereby reducing technical barriers and encouraging greater academic utilization. For Industrial Technology students, whose coursework frequently involves technical concepts, design activities, and problem-solving, the ability to obtain immediate explanations and instructional guidance through a simple conversational interface substantially increases the perceived educational usefulness of these technologies.

### 4.2 Perceived Ease of Use and Behavioral Intention

The study further revealed that Perceived Ease of Use directly influences Behavioral Intention, indicating that usability contributes not only indirectly through perceived usefulness but also independently shapes students' willingness to adopt AI language platforms. Students are more inclined to incorporate AI into their academic activities when they perceive the technology as accessible, convenient, and easy to learn.

This finding corroborates previous studies demonstrating that system usability remains an important determinant of technology adoption in educational settings **[12,16,23]**. Although contemporary university students generally possess high levels of digital literacy, cumbersome interfaces or complex interactions may still discourage sustained technology use. Consequently, developers of AI language platforms should continue emphasizing intuitive interface design, simplified user interactions, and personalized learning support to encourage broader adoption among students.

### 4.3 Perceived Usefulness as the Strongest Predictor of Behavioral Intention

Among the predictors of Behavioral Intention, Perceived Usefulness emerged as the strongest determinant, reinforcing one of the central propositions of the Technology Acceptance Model. Students are more likely to adopt AI language platforms when they perceive that these technologies improve academic performance, facilitate learning, increase productivity, and support successful completion of coursework.

This result is consistent with numerous studies reporting that perceived usefulness remains the dominant predictor of technology acceptance across educational technologies **[12,5,13,14]**. The finding suggests that students primarily evaluate AI language platforms according to their ability to solve authentic academic problems rather than merely their technological sophistication. Within Industrial Technology education, where students regularly engage with technical computations, engineering principles, laboratory procedures, and project development, AI language platforms provide timely explanations, instructional guidance, and problem-solving assistance that directly contribute to academic performance. Accordingly, higher education institutions should emphasize pedagogical applications that clearly demonstrate the educational benefits of generative AI rather than focusing solely on technological novelty.

### 4.4 The Role of Perceived Reliability in AI Adoption

The most important contribution of the present study lies in demonstrating that Perceived Reliability significantly influences students' Behavioral Intention to adopt AI language platforms. This finding extends the traditional Technology Acceptance Model by showing that students evaluate generative AI not only according to its usability and usefulness but also based on their confidence in the credibility, consistency, and accuracy of AI-generated information.

Unlike conventional educational technologies that primarily retrieve existing information, generative AI produces original responses that may occasionally contain factual inaccuracies, fabricated references, or hallucinated content. Consequently, students are unlikely to depend on AI-generated information unless they perceive it as sufficiently reliable for academic purposes. This finding supports recent arguments that trust-related constructs should be incorporated into technology acceptance models when investigating generative AI adoption **[18,17,19]**.

The significance of Perceived Reliability is particularly relevant within Industrial Technology education, where inaccurate technical information may negatively affect students' conceptual understanding, laboratory performance, and professional decision-making. Therefore, improving students' confidence in AI-generated information requires more than technological improvements. Universities should also strengthen AI literacy programs that teach students how to evaluate AI responses critically, verify information using authoritative sources, recognize AI limitations, and apply responsible AI practices in academic work. These educational interventions may substantially enhance students' confidence in generative AI while minimizing the risks associated with misinformation and overreliance.

### 4.5 Behavioral Intention and Actual Usage Frequency

Consistent with the Technology Acceptance Model, Behavioral Intention was found to be the strongest predictor of Actual Usage Frequency, indicating that students who intend to use AI language platforms are considerably more likely to integrate them into their everyday academic activities. This finding confirms that behavioral intention remains the immediate antecedent of actual technology use, as originally proposed by Davis **[12]**.

The result also aligns with recent studies examining AI adoption in higher education, which report that students with stronger intentions to use AI are more likely to employ these technologies for writing assistance, information retrieval, programming support, collaborative learning, and independent study **[1,8]**. The strong relationship observed in this study demonstrates that students' intentions translate into meaningful behavioral outcomes, highlighting the importance of cultivating positive perceptions toward AI technologies if universities seek to promote their effective educational integration.

### 4.6 Predictive Performance and Practical Significance

Beyond hypothesis testing, the present study contributes by evaluating the predictive capability of the Extended Technology Acceptance Model through PLS-Predict and Importance–Performance Map Analysis (IPMA). The satisfactory predictive performance indicates that the proposed model is capable of explaining future AI adoption behavior rather than merely describing existing relationships. This strengthens the practical value of the model for educational institutions seeking evidence-based strategies to support AI integration.

The IPMA results provide particularly meaningful managerial insights by identifying Perceived Reliability as a construct with substantial importance but comparatively lower performance. This suggests that institutional initiatives aimed at improving students' confidence in AI-generated information may produce greater gains in AI adoption than improvements focused exclusively on system usability. Universities should therefore prioritize AI literacy training, responsible AI guidelines, source verification practices, and instructional strategies that encourage critical evaluation of AI-generated outputs.

Overall, the findings indicate that successful implementation of generative AI in higher education requires a balanced approach that addresses technological usability, educational value, and information reliability. While ease of use and usefulness remain essential determinants of technology acceptance, the reliability of AI-generated information has emerged as a critical consideration that distinguishes generative AI from earlier educational technologies. By incorporating Perceived Reliability into the Technology Acceptance Model, this study advances a more comprehensive framework for understanding students' adoption of AI language platforms and offers practical guidance for institutions seeking to integrate generative AI responsibly into teaching and learning.

## 5. CONCLUSION

This study examined the factors influencing the adoption of generative AI language platforms among Bachelor of Science in Industrial Technology students by extending the Technology Acceptance Model (TAM) with Perceived Reliability. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the findings confirmed that all hypothesized relationships were significant, providing empirical support for the proposed Extended TAM.

Consistent with TAM, Perceived Ease of Use significantly influenced both Perceived Usefulness and Behavioral Intention, while Perceived Usefulness emerged as the strongest predictor of students' intention to adopt AI language platforms. More importantly, Perceived Reliability was found to be a significant determinant of Behavioral Intention, demonstrating that students consider not only the usefulness and ease of use of generative AI but also the accuracy, consistency, and credibility of AI-generated information. This finding extends the explanatory power of TAM and highlights the unique role of information reliability in generative AI adoption.

The study also confirmed that Behavioral Intention strongly predicts Actual Usage Frequency, indicating that positive perceptions translate into sustained educational use of AI language platforms. Furthermore, the results of PLS-Predict and Importance–Performance Map Analysis (IPMA) demonstrate that the proposed model possesses both explanatory and predictive value, with Perceived Reliability identified as a key area for institutional improvement.

Overall, the findings suggest that the successful integration of generative AI in higher education requires not only user-friendly and useful technologies but also strategies that strengthen students' confidence in the reliability of AI-generated information. By incorporating Perceived Reliability into TAM, this study contributes to the growing literature on generative AI adoption and provides a useful framework for promoting the responsible and effective use of AI in higher education.

## 6. Theoretical, Practical Implications, Limitations, and Future Research

This study extends TAM by incorporating Perceived Reliability as a significant determinant of Behavioral Intention toward generative AI language platforms. Beyond the traditional constructs of Perceived Ease of Use and Perceived Usefulness **[12]**, the findings demonstrate that students also consider the reliability and credibility of AI-generated information when deciding whether to adopt these technologies. The study further contributes empirical evidence from Industrial Technology education, an underexplored context where information accuracy is essential for technical learning and decision-making. In addition, the integration of PLS-Predict and IPMA strengthens the study by providing both explanatory and predictive insights.

From a practical perspective, the findings suggest that higher education institutions should complement AI adoption with AI literacy initiatives that promote critical evaluation, verification, and ethical use of AI-generated information. Educators should integrate AI into learning activities that foster critical thinking, while curriculum developers should embed AI evaluation competencies into technical programs. AI platform developers should likewise enhance system transparency, explainability, and source attribution to strengthen users' confidence in AI-generated content.

The study is limited by its cross-sectional design, reliance on self-reported data, and the use of respondents from a single Philippine state university, which may limit the generalizability of the findings. Future research should validate the proposed Extended TAM across diverse institutions and disciplines using longitudinal and multi-institutional designs. Additional constructs, including AI literacy, trust, perceived risk, ethical concerns, and facilitating conditions, should also be examined alongside objective usage data to further explain AI adoption. Overall, this study advances TAM by highlighting Perceived Reliability as a critical factor in generative AI adoption and provides practical guidance for the responsible integration of AI in higher education.

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