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Explaining Generative Artificial Intelligence Acceptance Among Indonesian University Students: an Extended Technology Acceptance Model

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ABSTRACT

The rapid integration of Generative Artificial Intelligence (GenAI) into higher education has transformed learning practices, creating a need to better understand the factors that influence students' acceptance of this emerging technology. While the Technology Acceptance Model (TAM) has been widely used to explain technology adoption, limited studies have incorporated contextual factors relevant to educational environments. This study extends TAM by integrating Value Compatibility (VC) and Lecturer Support (LS) to examine students' acceptance of GenAI in Indonesian higher education. A quantitative cross-sectional survey was conducted with 100 university students selected through purposive sampling. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 and a bootstrapping procedure of 5,000 subsamples. The findings reveal that Perceived Ease of Use significantly influences Perceived Usefulness, while Perceived Usefulness positively affects both Attitude Toward Using and Behavioral Intention. Attitude Toward Using significantly predicts Behavioral Intention, which subsequently influences Actual Use Behavior. Furthermore, the extended variables demonstrate significant effects, with Value Compatibility positively affecting Behavioral Intention and Lecturer Support enhancing Attitude Toward Using. The model exhibits moderate to high explanatory power and satisfactory predictive relevance. This study contributes to the technology acceptance literature by demonstrating that students' adoption of GenAI is shaped not only by technological perceptions but also by contextual and institutional factors. The findings provide practical insights for higher education institutions seeking to promote effective and responsible integration of GenAI into teaching and learning practices.

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Introduction

The emergence of Generative Artificial Intelligence (GenAI) a machine learning system capable of generating text, images, code, and multimedia content based on natural language instructions has brought about structural changes in the global higher education landscape.

Technologies such as ChatGPT represent a new generation of innovations based on large language models that have the potential to transform how students learn, interact with course materials, and build knowledge (Dai et al., 2023; Lo, 2023; Zhai, 2022). In the context of higher education, GenAI is beginning to be utilized to support personalized learning, the development of adaptive instructional materials, and the enhancement of academic process effectiveness, although it simultaneously raises serious challenges regarding academic integrity and the validity of the information it generates (Chiu, 2024; FuiHoon Nah et al., 2023; Sallam, 2023).

In the higher education setting, GenAI tools are both welcomed as personalized learning assistants and criticized as potential catalysts for academic dishonesty, the atrophy of critical thinking, and the homogenization of knowledge Dwivedi et al. (2023); FuiHoon Nah et al. (2023); Kasneci et al. (2023) identify a broad spectrum of implications: ranging from transformative benefits such as ondemand feedback, adaptive remediation, and access to guidance for underserved student populations to serious risks including factual content hallucinations, overreliance, and the erosion of deep learning dispositions. This dual nature of GenAI underscores that decisions regarding technology adoption must be based not merely on enthusiasm for innovation, but on rigorous empirical evidence regarding user acceptance, institutional context suitability, and ethical compatibility within the academic ecosystem. In the study of technology adoption systems, the Technology Acceptance Model (TAM) introduced by Davis (1989) remains one of the most widely used and validated theoretical frameworks across various technological contexts. TAM explains that perceived usefulness and perceived ease of use are the primary determinants influencing attitudes, intentions, and technology usage behavior. This model has proven to have strong explanatory power across various domains such as education, healthcare, and information systems, and continues to be adapted in the context of emerging technologies, including artificial intelligence (Dwivedi et al., 2023; FuiHoon Nah et al., 2023). Recent research also indicates that the TAM is relevant for explaining the adoption of GenAI in the context of higher education Chan (2023); Strzeleck, (2024), although there are still limitations to its application in developing countries.

Higher education institutions in Indonesia, including universities in Bandar Lampung, face a unique challenge: how to leverage the pedagogical efficiencies offered by GenAI while maintaining the quality of learning that is critical, reflective, and oriented toward the holistic development of students' competencies. The adoption of technology in educational settings cannot be separated from contextual factors such as infrastructure readiness, faculty members' digital competencies, and institutional values that shape the academic behavior of the academic community. The introduction of AI agents into this relational and experience based learning ecosystem raises fundamental questions that cannot be answered by standard TAM instruments alone.

In the context of higher education in Indonesia, the adoption of GenAI presents more complex challenges, particularly regarding infrastructure readiness, educators' digital competencies, and the academic culture that shapes students' learning behaviors. The integration of technology into learning depends not only on technical aspects but also on academic environmental factors that influence how students accept and use the technology. Contextual factors such as instructor support and the alignment of values in learning are crucial elements that can either strengthen or weaken the acceptance of technology in educational settings (Denny et al., 2023 ; Teubner et al., 2023).

Previous research in the field of educational technology has shown that technologybased learning tools can significantly increase student engagement and motivation when implemented with a clear pedagogical purpose (Anggelitha et al., 2025). In line with this, analyses of educational management at various institutions highlight that the adoption of technology is most effective when it aligns with the value system and academic culture of the community in question (Chualasta et al., 2025). Based on these foundational findings, this study aims to systematically examine whether and how students in Bandar Lampung accept GenAI tools, using a model that has been validated both theoretically and empirically.

This study addresses three main research questions: (1) Do Perceived Usefulness and Perceived Ease of Use significantly predict students' attitudes and behavioral intentions toward using GenAI tools in the learning process? (2) Do contextual factors specifically students' perceived alignment with the institution's academic values and the role of faculty encouragement moderate these core TAM relationships? (3) What evidencebased and contextsensitive recommendations can be formulated to support the effective integration of GenAI at universities in Bandar Lampung? The findings of this study are expected to contribute theoretically to the TAM literature in the context of higher education in developing countries, while also providing practical implications for institutional policies and curriculum development at universities in Indonesia and the ASEAN region.

Method

1. Research Design and Paradigm

This study employs a quantitative approach using a crosssectional survey design grounded in a positivist paradigm. This design was used to test the causal relationships among constructs derived from the Technology Acceptance Model (TAM) in the context of the acceptance of Generative Artificial Intelligence (GenAI) in learning. Data collection was conducted at a specific point in time using a structured questionnaire to ensure that all research variables could be measured objectively and in a standardized manner (Blut et al., 2022; Davis, 1989).

The research model consists of seven latent constructs, namely Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Using (ATU), Behavioral Intention (BI), Actual Use Behavior (AUB), Value Compatibility (VC), and Lecturer Support (LS). The first five constructs are core constructs in the TAM, while VC and LS are contextual constructs in the educational setting. VC represents the alignment of GenAI use with academic ethical values and learning responsibilities, while LS describes the support and encouragement provided by instructors regarding the use of learning technology.

The structural relationships tested include PEOU on PU, PEOU on ATU, PU on ATU, PU on BI, ATU on BI, BI on AUB, VC on BI, and LS on ATU. All constructs were operationalized as reflective constructs because the indicators were considered direct manifestations of the latent constructs. Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLSSEM) via SmartPLS 4, which is suitable for predictive models with complex constructs and without the assumption of data normality.

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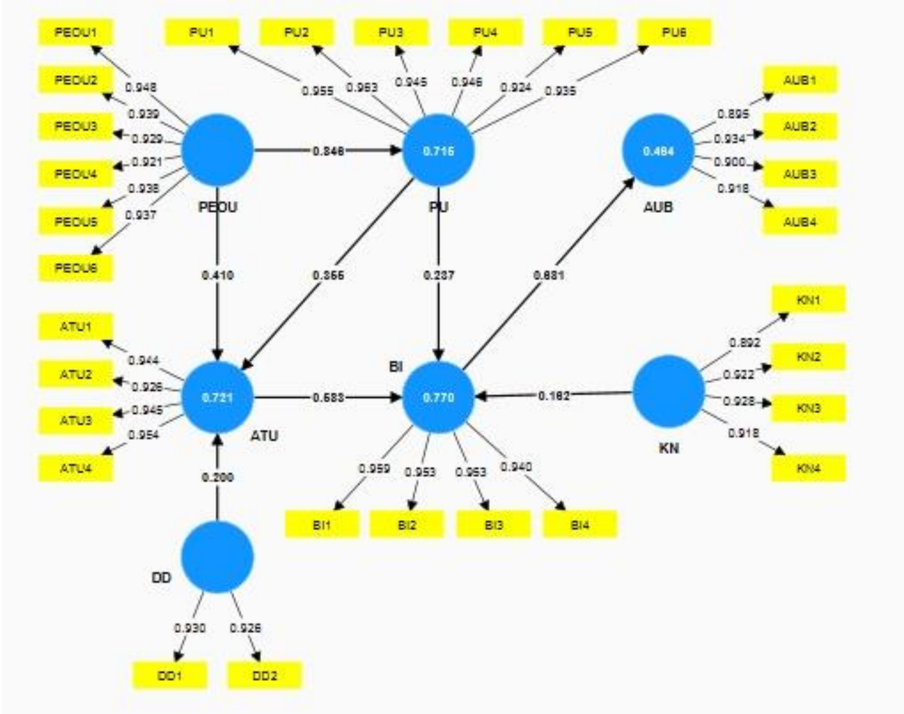

Figure 1 . Research Model Based on the Extended Technology Acceptance Model (TAM).

The conceptual model of this study is presented in Figure 1, which illustrates the relationships among constructs within the framework of the extended Technology Acceptance Model (TAM). The model shows the relationships between Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Using (ATU), Behavioral Intention (BI), and Actual Use Behavior (AUB), as well as two contextual constructs: Value Compatibility (VC) and Lecturer Support (LS). This model was used as the basis for hypothesis testing using the Partial Least Squares Structural Equation Modeling (PLSSEM) approach to simultaneously analyze the causal relationships among the variables in the study.

2. Population, Sample, and Sampling Procedures

The population in this study consists of 112 active students in higher education programs during the 2024/2025 academic year. This population consists of students in semesters 2 through 8 who generally have access to and exposure to the use of digital technology in the learning process. In the context of this study, the population is considered a relevant unit of analysis for examining the level of acceptance and use of generative artificial intelligence (GenAI) in the learning environment, given that all students have relatively homogeneous potential in the use of digital-based learning technology.

Sampling was conducted using purposive sampling, which involves selecting respondents based on specific criteria established in accordance with the research objectives. The inclusion criteria used were as follows: students must be actively enrolled at the time of the study, be in semesters 2 through 8, have experience using GenAI applications such as ChatGPT, Google Gemini, or Microsoft Copilot in academic activities, and have completed at least two core courses. These criteria were established to ensure that respondents had direct experience using GenAI, thereby enabling them to provide accurate assessments of the constructs measured in the research model particularly those related to perceptions of ease of use, benefits, attitudes, intentions, and technology usage behavior.

Based on the data collection results, a total of 100 valid respondents were identified and coded R001 through R100. All respondents fully completed the questionnaire covering the 30 research indicators without any missing data or invalid responses. This sample size met the minimum requirements for Partial Least Squares Structural Equation Modeling (PLSSEM) analysis, especially considering the complexity of the structural model, which consists of several latent constructs and relationships between variables tested simultaneously. Thus, the data obtained were deemed suitable and adequate for use in testing the research model and estimating parameters in the subsequent analysis stage (Hair et al., 2019).

3. Instrument Development

The research instrument in this study consists of 30 items designed to measure seven main constructs in the research model, namely Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Using (ATU), Behavioral Intention (BI), Actual Use Behavior (AUB), Value Compatibility (VC), and Lecturer Support (LS). Each construct was developed based on the Technology Acceptance Model (, TAM), which was expanded to include two contextual constructs to capture social and value factors within the learning environment. The distribution of items shows that PEOU and PU each consist of six indicators, ATU, BI, AUB, and VC each consist of four indicators, while LS consists of two indicators, resulting in a total of 30 items for the instrument.

Table 1 . Research Instrument Matrix

Construct	Indicator Code	Number
Perceived Ease of Use	PEOU1–PEOU6	6
Perceived Usefulness	PU1–PU6	6
Attitude Toward Using	ATU1–ATU4	4
Behavioral Intention	BI1–BI4	4
Actual Use Behavior	AUB1–AUB4	4
Value Compatibility	VC1–VC4	4
Lecturer Support	LS1–LS2	2
Total		30

Source: Developed by the researcher (2026) based on Davis (1989) and the TAM–GenAI literature

Conceptually, the PEOU indicator is used to measure respondents' perceptions of the ease of using GenAI in learning activities, including the ease of learning, understanding, and operating the technology. PU represents perceptions regarding the benefits of using GenAI in improving the effectiveness, efficiency, and quality of the learning process. Meanwhile, ATU is used to measure students' general attitudes toward the use of GenAI, BI measures behavioral intent to continue using the technology in the future, and AUB describes the level of actual use in daily academic activities.

In addition to the main TAM constructs, VC was developed to measure the alignment of GenAI use with academic ethical values, intellectual responsibility, and integrity in the learning process in general. The LS construct measures the extent to which faculty members

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provide support, guidance, and encouragement to promote the appropriate use of GenAI in a learning context. All indicators in this study were adapted from instruments validated in previous research Davis (1989); Strzelecki (2024) and tailored to the context of GenAI use in higher education.

The instrument development process involved content validation by experts and readability testing through cognitive interviews to ensure linguistic clarity, semantic appropriateness, and consistency in interpretation by respondents. All items were measured using a fivepoint Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Data review results showed that all responses fell within a valid range without any missing values or responses outside the measurement limits; therefore, the data were deemed suitable for further analysis using the PLSSEM model.

4. Data Analysis Procedure

Data analysis in this study was conducted using the Partial Least Squares Structural Equation Modeling (PLSSEM) approach with the assistance of SmartPLS 4 software. The analysis process was divided into two main stages: measurement model evaluation and structural model evaluation. The initial stage aimed to ensure that all indicators used in the study could accurately represent the latent constructs, while the second stage aimed to test the causal relationships among variables in the formulated research model.

The measurement model evaluation was conducted to assess the validity and reliability of the indicators. The tests included outer loading, Cronbach's alpha, composite reliability, rho_A, Average Variance Extracted (AVE), and the HeterotraitMonotrait Ratio (HTMT) (Hair et al., 2019). Indicators with an outer loading value of ≥0.708 are considered to make an adequate contribution to reflecting the latent construct. Convergent validity is deemed to be met if the AVE value is ≥0.50, while construct reliability is considered good if the Cronbach's alpha and composite reliability values are above 0.70. Meanwhile, discriminant validity was tested using the HTMT with a threshold of <0.85 to ensure that each construct exhibits clear empirical distinctions.

Furthermore, the structural model was evaluated using a bootstrapping procedure with 5,000 subsamples to produce stable estimates of path coefficients (β), t-statistics, and p-values. Relationships between variables were considered significant if the t-statistic was >1.96 and the p-value was <0.05. The structural relationships tested in this study included PEOU on PU, PEOU on ATU, PU on ATU, PU on BI, ATU on BI, BI on AUB, VC on BI, and LS on ATU. Model fit was evaluated using the coefficient of determination (R^2) for endogenous constructs, the effect size (f^2) for the contribution of each exogenous variable, and predictive relevance (Q^2) to assess the model's predictive ability. The model was also considered to have a good fit if the SRMR value was below 0.08. Product indicator analysis was not used in this study because all contextual variables (VC and LS) were treated as exogenous variables with a direct effect on the endogenous constructs in the structural model.

Findings

This section presents the research results obtained from data analysis to answer all research questions and test the previously formulated hypotheses. The research results are systematically organized based on the stages of analysis in Partial Least Squares Structural Equation Modeling (PLSSEM), which include measurement model evaluation

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and structural model evaluation. The presentation of results focuses on key inferential and predictive findings, rather than on raw data details, to provide a clear picture of the relationships among variables in the research model. Additionally, this section highlights the connection between the empirical results and the theoretical framework used and provides a basis for further discussion in the discussion section.

Descriptive Statistics

This study involved 100 valid respondents, all of whom completed the questionnaire in full for all research indicators. The data used consisted of 30 indicators representing seven main constructs, namely Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Using (ATU), Behavioral Intention (BI), Actual Use Behavior (AUB), Value Compatibility (VC), and Lecturer Support (LS).

In general, the descriptive results indicate that respondents have a relatively positive perception of the use of generative artificial intelligence in learning. This is reflected in the tendency for scores to fall within the moderate to high categories across all constructs, particularly for the PU and BI constructs, which indicate a strong tendency toward technology adoption in the learning environment.

Measurement Model Assessment

The evaluation of the measurement model indicates that all constructs in this study meet the validity and reliability criteria required for PLSSEM analysis. All constructs have Cronbach's alpha values ranging from 0.839 to 0.976, indicating a very high level of internal consistency for each latent variable measured. Furthermore, the composite reliability values both rho_A and rho_c also yielded very high results, exceeding 0.70, suggesting that the research instrument possesses strong and stable reliability.

Furthermore, the Average Variance Extracted (AVE) values for all constructs ranged from 0.831 to 0.905, indicating that each construct explains more than 83% of the variance in its indicators. This indicates that convergent validity has been very well established for all research constructs. The Behavioral Intention (BI) and Perceived Usefulness (PU) constructs showed the highest AVE values, reflecting the strength of these constructs in empirically representing the latent variables.

Table 2 . Reliability and Convergent Validity Assessment of Constructs

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATU	0.958	0.959	0.969	0.888
AUB	0.932	0.934	0.952	0.831
BI	0.965	0.966	0.975	0.905
DD	0.839	0.840	0.926	0.861
KN	0.936	0.940	0.954	0.838
PEOU	0.971	0.972	0.977	0.875
PU	0.976	0.976	0.980	0.892

Source: SmartPLS 4 Output

These results indicate that all research constructs have met the criteria for excellent reliability and convergent validity, as evidenced by the high values of Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) in the s for all latent variables.

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High internal consistency indicates that each indicator within each construct is able to measure the same concept stably and consistently, meaning there are no inconsistencies in the measurement instrument. Furthermore, the fulfillment of convergent validity indicates that the indicators within each construct have a strong ability to reflect the latent variables being measured, thus empirically confirming that the research constructs are welldefined.

Thus, it can be concluded that the measurement model used in this study is of good quality and meets the PLSSEM evaluation standards, both in terms of reliability and validity. These findings provide a strong basis for concluding that the data used in this study have met the methodological requirements to proceed to the next stage of analysis structural model assessment in order to evaluate the causal relationships among variables in the research model in greater depth and with greater inferential power.

Structural Model Assessment

The structural model assessment was conducted using the bootstrapping method with 5,000 subsamples to obtain stable estimates of path coefficients (β), tstatistics, and pvalues. The analysis results indicate that the relationships among variables in the research model exhibit varying levels of significance in accordance with the proposed hypotheses. Hypotheses 1 through 8 were tested based on the structural relationships among the constructs in the extended TAM model. The test results indicate that some relationships have a significant effect on the endogenous constructs, while others show a weaker effect depending on the statistical values obtained from the results.

Table 3 . Path Coefficients and Hypothesis Testing (Bootstrapping Results)

Hypotheses	Relationship	β (Original Sample)	tstatistic	pvalue	Decision
H1	PEOU → PU	0.846	26.999	0.000	Accepted
H2	PEOU → ATU	0.410	3,791	0.000	Accepted
H3	PU → ATU	0.355	3.526	0.000	Accepted
H4	PU → BI	0.237	2,581	0.010	Accepted
H5	ATU → BI	0.583	6.626	0.000	Accepted
H6	BI → AUB	0.681	12,608	0.000	Accepted
H7	VC (KN) → BI	0.162	2,502	0.012	Accepted
H8	LS (DD) → ATU	0.200	3.548	0.000	Accepted

Source: Primary data processed using SmartPLS 4 (Bootstrapping results)

The test results indicate that all hypotheses in the research model are accepted, as evidenced by tstatistic values exceeding the critical threshold of 1.96 and pvalues below 0.05. These findings confirm that all constructs in the model have a significant influence on explaining the acceptance and use of Generative Artificial Intelligence in learning. Thus, this research model has strong predictive power and supports the Technology Acceptance Model framework expanded with contextual factors.

Coefficient of Determination (R^2) and Model Fit

The model's ability to explain the variance of the endogenous construct was evaluated using the coefficient of determination (R^2), while its predictive ability was assessed using Stone–Geisser's predictive relevance (Q^2). The results in Table 3 show that the R^2 value for the Behavioral Intention (BI) construct is 0.770, meaning that 77.0% of the variance in BI

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can be explained collectively by Perceived Usefulness (PU), Attitude Toward Using (ATU), and Value Compatibility (VC). The Attitude Toward Using (ATU) construct has an R^2 value of 0.721, indicating that 72.1% of the variance in ATU is explained by Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Lecturer Support (LS). Furthermore, the R^2 value for PU of 0.715 indicates that PEOU explains 71.5% of the variance in PU, while the R^2 value for Actual Use Behavior (AUB) of 0.464 indicates that Behavioral Intention explains 46.4% of the variance in actual usage behavior. The relatively small difference between the R^2 and adjusted R^2 values indicates that the model's stability is maintained after accounting for the number of predictors in each endogenous construct.

Table 4 . Coefficient of Determination and Predictive Relevance

Endogenous Construct	R^2	Adjusted R^2	Q^2	Interpretation
ATU	0.721	0.712	0.631	Moderate–substantial explanatory power; strong predictive relevance
AUB	0.464	0.458	0.379	Weak–moderate explanatory power; predictive relevance established
BI	0.770	0.763	0.685	Substantial explanatory power; strong predictive relevance
PU	0.715	0.712	0.627	Moderate–substantial explanatory power; strong predictive relevance

Source: Primary data processed using SmartPLS 4.

All endogenous constructs have Q^2 values greater than zero, ranging from 0.379 to 0.685, indicating that the model has good predictive relevance for ATU, AUB, BI, and PU. The highest Q^2 value was found for BI at 0.685, followed by ATU at 0.631 and PU at 0.627, while AUB had a Q^2 value of 0.379. Thus, the model is not only capable of adequately explaining the variance of the endogenous constructs but also demonstrates strong predictive power regarding the acceptance and use of GenAI in learning.

Table 5 . Model Fit Assessment

Fit Index	Saturated Model	Estimated Model	Assessment
SRMR	0.040	0.058	Acceptable
d_ULS	0.728	1.561	Descriptive report
d_G	1.169	1.200	Descriptive report
Chisquare	625.952	633.558	Descriptive report
NFI	0.857	0.855	Below the conventional threshold of 0.90

Source: Primary data processed using SmartPLS 4.

Model fit evaluation shows that the SRMR value of the estimated model, at 0.058, is below the threshold of 0.08, indicating that the model has a good level of fit. The NFI value of 0.855 is slightly below the benchmark of 0.90, but is still acceptable in the context of PLSSEM because it is sensitive to sample size and model complexity. Meanwhile, d_ULS and d_G are presented descriptively because a more accurate interpretation requires comparison with bootstrap confidence interval values. Therefore, the evaluation of model quality is primarily based on SRMR, R^2, Q^2, and the significance of structural relationships within the model.

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Summary of Key Findings

Overall, the results of this study indicate that the acceptance of Generative Artificial Intelligence (GenAI) in an educational context can be comprehensively explained through the Technology Acceptance Model (TAM) framework, expanded to include contextual variables: Value Compatibility (VC) and Lecturer Support (LS). All structural relationships tested in the research model were found to be significant, indicating that the technology adoption process is influenced not only by individual cognitive factors such as perceptions of ease of use and benefits but also by attitudinal factors, behavioral intentions, and academic environmental conditions that shape the overall technology usage ecosystem. Thus, this research model provides strong empirical support for the validity of TAM in explaining technology acceptance behavior in an artificial intelligencebased higher education environment.

The main findings show that Perceived Ease of Use (PEOU) has a very strong influence on Perceived Usefulness (PU), confirming that ease of use is a fundamental factor in shaping perceptions of technology's benefits. When users feel that a technology is easy to understand and operate, their perception of the technology's usefulness in supporting learning activities increases significantly. Furthermore, Perceived Usefulness (PU) was found to have a significant positive influence on Attitude Toward Using (ATU) and Behavioral Intention (BI), indicating that the perception of benefits not only fosters a positive attitude toward the technology but also strengthens an individual's intention to use it consistently in an academic context.

Moreover, Attitude Toward Using (ATU) serves as a key determinant influencing Behavioral Intention (BI), which in turn directly contributes to Actual Use Behavior (AUB). This chain of relationships confirms that an individual's attitude toward technology serves as a crucial mediator in bridging the gap between cognitive perceptions and actual GenAI usage behavior. Thus, the intention to use does not arise spontaneously but is formed through a structured cognitive and affective evaluation process, which ultimately drives the realization of technology usage behavior in daily learning activities.

In addition to technological and psychological factors, the results of this study also underscore the important role of contextual factors in reinforcing the technology acceptance model. Value Compatibility (VC) was found to have a significant influence on Behavioral Intention (BI), which indicates that the alignment between technology and academic values as well as learning ethics is a key factor in shaping individuals' readiness to adopt GenAI. On the other hand, Lecturer Support (LS) has a significant effect on Attitude Toward Using (ATU), indicating that lecturer support in the learning process acts as a key catalyst in shaping students' positive attitudes toward technology use. Overall, these findings demonstrate that technology adoption in education is not merely an individual process but also the result of the interaction between technological, psychological, and institutional factors.

Discussion

The results of this study show that the acceptance of generative artificial intelligence in a learning context is strongly influenced by factors within the Technology Acceptance Model (TAM), particularly perceived ease of use (PEOU) and perceived usefulness (PU). These findings confirm that ease of use is a significant initial determinant in shaping perceptions of usefulness, which ultimately reinforces attitudes and intentions toward technology use.

The significant and strong relationship between PEOU and PU indicates that when users perceive a technology as easy to use, their perception of its usefulness in supporting learning activities increases substantially. This aligns with the fundamental principle of TAM, which positions ease of use as the primary antecedent of perceived usefulness in the formation of technology acceptance.

In addition to technological factors, the research results also show that user attitude (attitude toward using) and behavioral intention play an important mediating role in bridging the relationship between perceived usefulness and actual use. The significant influence of ATU on BI indicates that a positive attitude toward GenAI directly strengthens the intention to use it in learning activities. Furthermore, the relationship between BI and actual use behavior (AUB) demonstrates that the intention to use makes a tangible contribution to driving technology adoption at the level of actual behavior. This finding reinforces the consistency of the TAM model, which posits that intention is the primary predictor of technology use behavior.

The findings of this study also underscore the importance of contextual factors in the learning environment. Value compatibility (VC) was found to have a significant influence on behavioral intention, indicating that alignment between technology and academic values plays a crucial role in shaping individuals' readiness to adopt GenAI. Meanwhile, lecturer support (LS) was found to influence attitude toward using, suggesting that support from instructors contributes to fostering a positive attitude toward technology use. These results indicate that technology acceptance is determined not only by technical factors but also by a social and academic environment that supports the purposeful use of technology.

Overall, the research model shows that a combination of technological, psychological, and contextual factors provides a strong explanation for GenAI adoption behavior in learning. The coefficient of determination values for the endogenous constructs indicate that the model has good predictive power, meaning that can be used to explain patterns of technology adoption in the context of modern education. These findings expand the TAM literature by demonstrating that, in the context of artificial intelligence-based learning, environmental factors such as instructor support and value congruence play a significant role in strengthening the technology adoption process.

Conclusion

The findings demonstrate that the extended Technology Acceptance Model (TAM), incorporating Value Compatibility and Lecturer Support, effectively explains students' acceptance of Generative Artificial Intelligence (GenAI) in higher education. Perceived Ease of Use and Perceived Usefulness remain the primary drivers of students' attitudes, behavioral intentions, and actual use of GenAI, while Value Compatibility and Lecturer Support significantly strengthen technology acceptance by reflecting the influence of educational values and the academic environment. These findings extend the explanatory power of the traditional TAM by demonstrating that students' acceptance of GenAI is shaped not only by technological perceptions but also by contextual factors that support meaningful and sustainable AI integration into higher education. The study therefore provides empirical evidence that successful GenAI adoption requires a balance between technological quality, institutional support, and alignment with educational values.

These findings have important implications for higher education institutions seeking to integrate GenAI into teaching and learning. Universities should prioritize the development of user-friendly AI-supported learning environments, strengthen lecturers' capacity to facilitate responsible AI use, and promote digital learning policies that align AI implementation with educational objectives and academic integrity. Although the proposed model provides strong explanatory evidence, the findings are limited by the cross-sectional research design and the characteristics of the study sample. Future research should validate the model across diverse educational contexts using longitudinal or mixed-method approaches and incorporate additional constructs, such as AI literacy, trust in AI, ethical awareness, self-regulated learning, and institutional readiness, to develop a more comprehensive understanding of students' acceptance and sustainable use of Generative Artificial Intelligence.

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