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Determining factors influencing undergraduate students' intention to use AI-powered learning platform on academic learning in higher education Indonesia

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Abstract

Artificial Intelligence (AI) has emerged as a transformative force in higher education, enabling adaptive and personalized learning experiences. Despite its potential, student adoption of AI-powered learning platforms remains inconsistent, particularly in developing contexts. This study explores the determinants influencing Indonesian undergraduate students' intention to use AI-powered learning platforms based on the Technology Acceptance Model (TAM). Data were collected from 200 undergraduate students in Surakarta, Indonesia, using a structured online questionnaire and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrate that perceived ease of use (PEOU) and perceived usefulness (PU) significantly influence attitude toward use (AT) and behavioral intention (BI). Additionally, AT mediates the relationships between PEOU, PU, and BI. The model exhibited high internal consistency and explanatory power (R^2 = 0.598 for AT, R^2 = 0.430 for BI), confirming the relevance of TAM in the context of AI-enhanced learning. These findings underscore the importance of designing AI learning platforms that are both usable and beneficial, supporting educators and policymakers in fostering effective technology integration in higher education.

Keywords: Determining factors influencing, Use AI-powered, Learning platform on academic learning

Introduction

The rapid advancement of Information and Communication Technology (ICT) is transforming the global educational landscape, heralding an era where artificial intelligence (AI)-powered learning platforms are increasingly used to enhance the academic experience. Silva et al. (2024) emphasized that this transformation overcomes educational limitations by creating adaptive learning environments. Globally, educational institutions are integrating these technologies to meet the growing demand for personalized learning, improved accessibility, and efficient information delivery. Mahawar et al. (2025) argued that ICT integration revolutionized education by enabling flexible, personalized learning that transcends barriers. he proliferation of AI in education is driven by its potential to provide tailored learning pathways, real-time feedback, and cognitive support tools, empowering learners to overcome the limitations of traditional classrooms. Salem (2024) demonstrated that AI-driven personalized learning significantly enhances student engagement and academic performance through adaptive algorithms that customize content to individual learning needs and preferences.

Despite these promising developments, the adoption and sustained use of AI-powered academic platforms remain inconsistent, limited by several contextual factors. Prior studies indicate that technology adoption in higher education frequently encounters obstacles such as perceived complexity, lack of familiarity, and hesitation to rely on digital solutions for core learning activities. Feng et al. (2025) identified that technological infrastructure, ease of use, institutional support, and socio-cultural factors serve as key determinants influencing technology adoption among students. In Indonesia, where digital transformation is rapidly reshaping educational norms, active undergraduate students have become notable adopters of AI-driven learning tools. In Indonesia, this digital transformation is rapidly reshaping educational norms, and undergraduate

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students are notable adopters of AI-driven learning tools. As Sumartias et al. (2024) note, this transformation is essential for producing competent graduates with strong digital competencies. However, the specific drivers of students' intention to use these platforms are not yet fully understood. Ansari et al. (2024) revealed that an intricate interaction of factors affects educational technology adoption, including lack of technological resources and infrastructure, collaboration barriers, data security concerns, accessibility issues, and insufficient training and technological assistance. This gap highlights the need to examine the determinants of technology acceptance among Indonesian students, whose academic needs and technological awareness create a unique context for study. Das et al., (2025) demonstrated that understanding the psychological tendencies of users toward technology and the quality aspects of AI-enhanced learning platforms is crucial for ensuring effective implementation and successful adoption in educational settings.

Focusing specifically on undergraduate students in Indonesia, particularly those who have experience using AI-based platforms for academic purposes, this research addresses the need to understand the factors that drive or hinder technology adoption in educational contexts. The choice of this group is based on their high degree of exposure to digital resources and familiarity with seeking academic support through AI technologies, positioning them as a relevant and insightful cohort for investigation.

This study aims to investigate and identify the key factors that influence undergraduate students' behavioral intention to adopt AI-powered learning platforms for academic purposes within the Indonesian higher education context. This investigation is guided by the following research question: What factors significantly determine Indonesian undergraduate students' intention to use AI-powered learning platforms for academic learning activities?

To address this research question systematically, this study is grounded in the Technology Acceptance Model (TAM). Specifically, it adopts the framework that posits Perceived Usefulness (PU) And Perceived Ease Of Use (PEU) as key determinants of users' Attitude Toward use (AT), which in turn influences their behavioral intention (BI) (Venkatesh et al., 2003). The TAM framework frames technology adoption in terms of Perceived Usefulness (PU), Perceived Ease Of Use (PEU), Attitude Toward use (AT), and Behavioral Intention (BI). The TAM framework has demonstrated robust explanatory power for technology integration in education, consistently highlighting PU and PEU as key predictors of user attitude and intention (Marangunić & Granić, 2015, jam et al., 2025). In line with prior research and instrument validation, this study employs the revised TAM constructs to investigate the direct and indirect relationships among these variables.

Building on these theoretical foundations, the following research hypotheses are proposed:

H1: Perceived Ease of Use (PEOU) has a positive and significant effect on students' Attitude Toward Using (AT) AI-powered learning platforms.

H2: Perceived Ease of Use (PEOU) has a positive and significant effect on Perceived Usefulness (PU) of AI-powered learning platforms.

H3: Perceived Usefulness (PU) has a positive and significant effect on students' Attitude Toward Using (AT) AI-powered learning platforms.

H4: Attitude Toward Using (AT) has a positive and significant effect on students' Behavioral Intention (BI) to use AI-powered learning platforms.

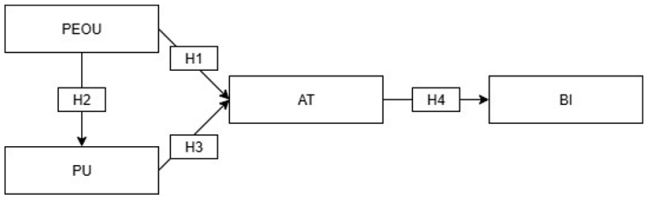

Figure 1. Conceptual framework of factors influencing students' intention to use ai-powered learning platforms based on the technology acceptance model (TAM)

The significance of this study lies in its potential to provide empirical insights into AI technology adoption in Indonesian higher education. By identifying the key factors that drive or hinder students' use of AI-powered learning tools, this research offers valuable guidance for academic

developers, policy makers, and educators in the designing, implementing, and promoting effective digital solutions.effective digital solutions. Furthermore, the findings contribute to the existing body of knowledge surrounding technology acceptance in developing country contexts, emphasizing practical strategies to foster engagement and enhance learning outcomes through responsible and student-centered technological innovation.

Research Method

To answer the research questions asked, this study uses a quantitative approach with the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis technique. The selection of this method was based on its reliability in handling complex models as well as its ability to comprehensively analyze causal relationships. PLS-SEM has been widely used in the field of education, especially in research related to technology integration with the Technology Acceptance Model (TAM) approach (Sasongko et al., 2024), so it is relevant to be used in the context of this research .

Data collection, respondents and research instruments

Prior to initiating our research, we secured ethical clearance for the study. Following this approval, we implemented a web-based survey as our data collection instrument, selected for its administrative simplicity and compatibility with multiple electronic devices (Fraenkel & Wallen, 2009; Fatima et al., 2025). The data in this study was collected through a closed questionnaire in the form of an online questionnaire using Google Form by sending a link to participants and keeping the questionnaire active for four weeks. The population in this study is active students in the city of Surakarta, the questionnaire was disseminated to students at the Strata 1 (S1) level from various study programs. The selection of S1 students as respondents was based on their high level of awareness of artificial intelligence (AI) technology, as well as the fact that they have become accustomed to using AI platforms in material search activities and learning support. The sampling technique used is purposive sampling, with the criteria for respondents to be active students who have experience using AI-based platforms for academic purposes.

According to (Wang et al., 2019), questionnaire is a widely used method in studies of technology acceptance. The question items were designed based on the five constructs (PU, PEU, AT, and, BI) of the model. This questionnaire demonstrated strong reliability and validity, as indicated by loading factor values exceeding 0.7 for all items. We labelled the five scale questions as ‘Strongly Disagree’ , ‘Disagree’ ‘Neutral’, ‘Agree, and ‘Strongly Agree’ , and they were ranged from 1 to 5, respectively. This research instrument has been translated into Indonesian and adapted to the context and characteristics of the respondents involved in this study, making the instrument relevant and easy for participants to understand. In order to assess content validity of the constructs, the questionnaire was reviewed by two experts. The instrument was examined through content validity index. The experts were requested to examine if the items covered all related aspect. The results showed that the average score of the item above the threshold value which is 0.800 (Halek et al., 2017). Furthermore, all items values were above the threshold values of 0.780. Furthermore, a pilot test was carried out with eight selected students. After the students completed the questionnaire, they were interviewed to make sure that they understood the questions and that questionnaire items made sense for them. The questions were then revised according to comments from the interviewees.

Data analysis

The data analysis in this study was carried out using SmartPLS software version 3.0. The analysis stages include testing measurement models (outer models), structural models (inner models), and hypothesis testing. In the outer model testing stage, an evaluation was carried out on the validity of the indicator using the outer loading value, the validity of the construct through the Average Variance Extracted (AVE) value, and the reliability of the construct through the Composite Reliability (CR) value and Cronbach's Alpha. Furthermore, the inner model test was carried out to evaluate the strength of the structural model through the determination coefficient value (R^2) and the measurement of the overall quality of the model through the Goodness of Fit (GoF) value. Finally, hypothesis testing was carried out using the bootstrapping method to

determine the level of significance of the relationship between variables in the proposed model.

Results and Discussion

Result

Data collection through questionnaires given to students resulted in as many as 200 respondents. Of these, 103 male respondents were present, while female respondents were 97 people. Based on demographic data, the majority of respondents came from urban areas, namely 111 students. Meanwhile, 64 students came from suburban areas, and 25 students came from rural areas.

In addition to regional demographic data, the questionnaire also includes information about the time of mobile phone use most often done by respondents. The results showed that most students used mobile phones more often at night, with a total of 94 respondents. Meanwhile, the use of mobile phones in the morning was the least, namely only 42 respondents.

Table 1. Demographic characteristics of respondents

Category	Subcategory	Number of Respondents
Gender	Male	103
	Female	97
Area of Origin	Urban	111
	Suburban	64
	Rural	25
Phone Usage Time (Most Often)	Night	94
	Morning	42

These findings indicate that nighttime is a moment where students have more free time, so they tend to use it to surf the internet or use their mobile phones. On the other hand, in the morning, student activities tend to be more congested with activities such as lectures or other academic activities, so the time to use mobile phones becomes more limited.

Measurement model

After the analysis was carried out using SmartPLS 3.0 software, good results were obtained from the outer model test, which aims to test the reliability and validity of the instruments used in the study (Hair et al., 2019). The first test was carried out by paying attention to the loading factor value of each variable in the study. The results of the analysis showed that all loading factor values met the set threshold, which was more than 0.700 (Hair et al., 2019).

Table 2. Results of Outer Model (Measurement Model) Evaluation

Variabel	Factor loading's	CR	Cronbach alpha	AVE
Attitude Toward	0,719-0,863	0,912	0,879	0,675
Behavioral Intention to use	0,887-0898	0,887	0,745	0,797
Perceived Ease of Use	0,773-0,848	0,911	0,878	0,673
Perceived of Usefulness	0,776-0,887	0,916	0,885	0,687

Furthermore, convergent validity is measured through the Average Variance Extracted (AVE) value. The AVE values obtained from all variables in the study showed a number above 0.5, which means it met the convergent validity criteria. To test the validity of the discriminant, the Heterotrait-Monotrait Ratio (HTMT) approach was used, with a maximum limit of 0.90. The results of the analysis showed that all HTMT values were below this threshold, so it can be concluded that the validity of the discriminant has also been met.

Table 3. Results of Discriminant Validity Test Using Heterotrait-Monotrait Ratio (HTMT)

	AT	BI	PEOU	PU
AT				
BI	0,809			
PEOU	0,807	0,617		
PU	0,791	0,634	0,755	

In assessing the reliability of the instrument, two main indicators are used, namely Cronbach's Alpha and Composite Reliability values. Both show values above 0.700, which indicates that the instrument has a good level of internal consistency. Thus, based on all the tests that have been carried out, it can be concluded that the instruments used in this study are valid and reliable, so they are suitable for further research purposes.

Inner model testing

In addition to *testing the outer model* and hypothesis, the analysis in this study also includes testing *the inner model* by looking at *the R-square* (R^2) and *Goodness of Fit* (GoF) values to assess the overall predictive strength of the model. The R^2 value is used to measure how much an independent variable is able to explain the variation of the dependent variable. The GoF value is used as an indicator of the extent to which the overall structural model matches the data obtained (Hair et al., 2019).

Table 4. Results of R^2 and goodness of Fit (GoF) evaluation

Value R^2		
	R Square	**R Square Adjusted**
AT	0,598	0,594
BI	0,430	0,427
PU	0,452	0,449
Value GoF		
	Saturated Model	**Estimated Model**
SRMR	0,062	0,063

The test results showed (Table ..) that the R^2 value for the Attitude (AT) variable was 0.598, with *the adjusted R^2* of 0.594. This means that 59.8% of the variation in user attitudes can be explained by the variables in the model, namely Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Furthermore, the R^2 value for the Behavioral Intention (BI) variable was 0.430, with *an adjusted R^2* of 0.427, indicating that 43% of the variation in use intent was explained by AT, PEOU, and PU. Meanwhile, the R^2 value for the Perceived Usefulness (PU) variable was 0.452 with *an adjusted R^2* of 0.449, which means that about 45.2% of the PU variation can be explained by PEOU.

To assess the overall suitability of the model, the Standardized Root Mean Square Residual (SRMR) value was used as part of the *Goodness of Fit test*. The results of the analysis showed an SRMR value of 0.062 for *the saturated model* and 0.063 for the *estimated model*. Since the SRMR value is below the threshold of 0.08 (Hair et al., 2019), it can be concluded that the model used in this study has a good degree of compatibility between theoretical models and empirical data. Thus, based on the R^2 and GoF values, this research model is considered to have strong predictive power and is suitable to be used to describe the relationship between variables in the context of the research conducted.

Hypothesis testing

Hypothesis testing in this study was carried out using *a bootstrapping technique* with a significance level of 5% (t> value of 1.96). The results of the analysis showed that all hypotheses submitted were accepted because the *p-value* was below 0.05. In particular, the direct influence between variables showed significant results. First, attitude (Attitude/AT) has a significant effect on use intention (Behavioral Intention/BI) with a coefficient value of 0.656 (t = 10.179; p = 0.000). This shows that the more positive the students' attitude towards the system, the higher their intention to use it. Furthermore, the perception of Perceived Ease of Use (PEOU) significantly affected attitude (AT) with a coefficient of 0.712 (t = 13.687), and directly also affected the intention of use (BI) with a coefficient of 0.467 (t = 7.161). This shows that students who find the system easy to use will have a more positive attitude and intention towards its use.

Table 5. Results of hypothesis testing

	Original Sample (O)	**T Statistics**	**P Values**
AT → BI	0,656	10,179	0,000
PEOU → AT	0,712	13,687	0,000
PEOU → BI	0,467	7,161	0,000
PEOU → PU	0,672	12,669	0,000
PU → AT	0,407	6,509	0,000
PU → BI	0,267	5,117	0,000
PEOU → AT → BI	0,288	5,531	0,000
PU → AT → BI	0,267	5,117	0,000
PEOU → PU → AT → BI	0,180	4,429	0,000

In addition, PEOU also has a significant influence on the perception of usefulness (PU), with a coefficient value of 0.672 (t = 12.669), which means that systems that are considered easy to use tend to be more useful as well. PU itself has a direct influence on attitude (AT) with a coefficient of 0.407 (t = 6.509), as well as on intention to use (BI) with a coefficient of 0.267 (t = 5.117). This means that the system that is perceived to be useful encourages the formation of positive

attitudes and increases the intention to use.

For indirect influences, the results also showed a significant mediating relationship. Attitude (AT) was shown to mediate the relationship between PEOU and BI (coefficient 0.288; t = 5.531), as well as mediating the relationship between PU and BI (coefficient 0.267; t = 5.117). In addition, there is also a tiered mediation path from PEOU through PU and AT to BI, which is also significant (coefficient 0.180; t = 4.429). This shows that the perception of ease of use influences the intention of use indirectly through increased perception of usability and positive attitudes towards the system.

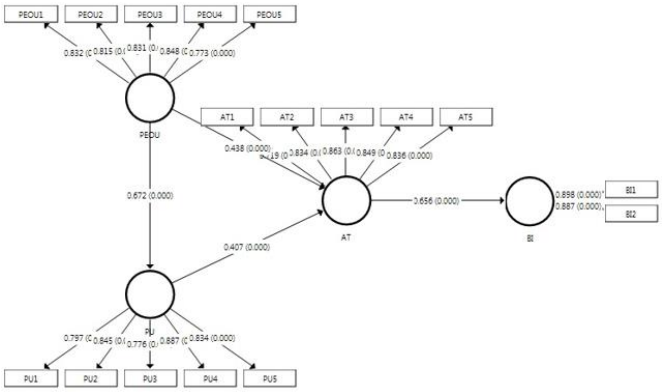

Figure 2. Structural model results of ai-powered learning platform adoption

Overall, these results support all hypotheses in the study and show that both the perception of ease of use and usability have an important role in shaping students' attitudes and intentions in using the system.

Discussion

The results of this study strengthen the *Technology Acceptance Model* (TAM) developed by Davis (1989), where *Perceived Ease of Use* (PEOU) and *Perceived Usefulness* (PU) are proven to have a significant influence on *Attitude* (AT) and *Behavioral Intention* (BI). These findings are in line with previous research by (Jo, 2022) which stated that the perception of convenience and usability is a major determining factor in technology adoption, especially in the context of higher education. Students who feel that AI-based platforms are easy to use and useful tend to have a more positive attitude and a stronger intention to continue using them.

Specifically, the direct influence of PEOU on AT (β = 0.712) and BI (β = 0.467) shows that ease of use plays a dual role, both in shaping attitudes and in encouraging intentional behavior. This emphasizes the importance of a user-friendly interface and intuitive system design in attracting students' interest. PU also plays an important role in influencing AT (β = 0.407) and BI (β = 0.267), supporting the findings of (Tanadi et al., 2015), which states that perceptions of the benefits of a system are a strong driver in shaping sustainable use intentions.

Interestingly, the results of the mediation pathway in this study show that AT significantly mediates the influence of PU and PEOU on BI. This reinforces the view that although Technology may seem useful and easy, but user attitudes remain the key link that determines whether someone will actually intend to use it. The findings of tiered mediation from PEOU → PU → AT → BI also make an important theoretical contribution, namely the logical flow that the perception of convenience encourages the perception of usability, which then forms a positive attitude and ultimately gives rise to the intention of use. These findings are in line with the TAM model modified and developed by (Venkatesh et al., 2003) in *the Unified Theory of Acceptance and Use of Technology* (UTAUT).

This research indicates that in the context of Indonesian students who are increasingly familiar with technology, especially AI-based platforms for academic purposes, the convenience and usability factors are more crucial than other external factors. Students not only want a sophisticated system, but also a system that does not burden their cognition in the process of using it. Therefore, developers of AI-based educational technology need to consider these two aspects as the foundation of product design.

Conclusion

This study emphasizes that attitudes, perceptions of ease, and perception of usability are key determinants in shaping students' intentions to use AI-based platforms in learning. The strong validity of the model suggests that *the Technology Acceptance Model* (TAM) approach remains relevant to explain technology adoption behavior in the era of artificial intelligence.

Practically, developers of AI platforms are advised to

prioritize simple interfaces, as well as features that directly support students' academic needs. This can increase the user's comfort and confidence from the beginning of use. Not only that, lecturers as facilitators can integrate AI in learning to make it more interactive.

However, this study has limitations in the context of the sample that only includes undergraduate students from one geographical area, so the risk of generalizing the results to a wider population needs to be done carefully. Advanced research can consider variations in institutional backgrounds and educational levels for more comprehensive outcomes.

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