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Learning Autonomy and Effectiveness in AI-Supported Engineering Education Integrating Technology Acceptance and Motivation

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ABSTRACT

Purpose – This study examines the influence of learning autonomy on learning effectiveness in artificial intelligence supported learning among engineering students by extending the Technology Acceptance Model with motivational and psychological factors.

Design/methods/approach – A quantitative cross-sectional survey was conducted involving 90 engineering students from a public university in Indonesia who had experience using artificial intelligence tools for academic learning. Data were analyzed using partial least squares structural equation modeling to examine the relationships among perceived usefulness, self-efficacy, willingness for autonomous learning, and learning effectiveness and autonomy.

Findings – The results indicate that perceived usefulness, self-efficacy, and willingness for autonomous learning all have significant positive effects on learning effectiveness and autonomy. Willingness for autonomous learning emerged as the strongest predictor, highlighting the central role of students' internal motivation and readiness to manage their own learning processes in AI-supported environments.

Research implications/limitations – The study is limited by its cross-sectional design, reliance on self-reported data, and a sample restricted to engineering students from a single institution, which may limit generalizability.

Originality/value – This study extends the Technology Acceptance Model by integrating learning autonomy and motivational factors within an artificial intelligence supported learning context, offering empirical evidence to inform the design of balanced and student-centered AI-enhanced learning in higher education.

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INTRODUCTION

The development of Artificial Intelligence in Education (AIED) in higher education has shown a significant increase in line with digital transformation, which has driven the use of adaptive learning systems, learning analytics, and artificial intelligence based learning assistants to support students' learning processes (S. Wang et al., 2024). In line with this development, the use of Artificial Intelligence (AI) in education has continued to increase and has substantially transformed the way students learn. However, excessive reliance on technology has the potential to reduce students learning independence, critical thinking skills, and learning initiative (Parreira et al., 2021; Sutrisno et al., 2023). The study *The Impact of AI Usage on University Students* indicates that students willingness to engage in independent learning remains at a moderate level, with a mean score of 3.276 and a standard deviation of 1.069, suggesting that learning independence has not yet reached an optimal level despite the increasing use of AI (L. Wang & Li, 2024). Therefore, it is important to analyze the influence of Artificial Intelligence in Education (AIED) on the effectiveness and independence of student learning in the digital era.

The literature review shows that research on AI in education mainly focuses on two primary themes: efficiency enhancement and technology acceptance. AI has been proven to improve learning efficiency, expand access to information, and demonstrate its potential in supporting students' learning autonomy (Ardana et al., 2025; Aulia & Purmadi, 2025). The implementation of Artificial Intelligence in higher education significantly contributes to improving learning effectiveness, particularly in terms of conceptual understanding, learning time efficiency, and student engagement in the learning process (S. Wang et al., 2024; Merino-Campos, 2025). AI-based learning systems enable the provision of real-time feedback and personalized learning recommendations tailored to individual student needs, thereby supporting more adaptive and personalized learning processes and allowing adjustments in learning strategies according to individual requirements (S. Wang et al., 2024). However, several studies have emphasized that improvements in learning efficiency resulting from AI use are not always accompanied by increased student learning autonomy (Darmono et al., 2025). In certain contexts, intensive use of AI may encourage student dependence on intelligent systems, particularly when AI replaces reflective thinking and independent problem-solving processes (Merino-Campos, 2025). These findings indicate that the impact of AI on learning is highly dependent on the context of use, student characteristics, and instructional design applied in higher education institutions(Darmono et al., 2025).

From a theoretical perspective, the Technology Acceptance Model (TAM) remains the dominant and most widely used framework for explaining the adoption and use of learning technologies, including AI-based systems, in higher education environments (Xue et al., 2025; Zhao et al., 2025). TAM emphasizes that perceived usefulness and perceived ease of use are the main determinants shaping users' attitudes and intentions toward learning technologies (Zhao et al., 2025). However, this model does not adequately consider psychological factors such as self-efficacy and willingness to engage in independent learning, which have been shown to influence the effectiveness of technology use (Al-Maroof et al., 2020; Sari et al., 2025). Therefore, the TAM must be modified by incorporating psychological factors to provide a more comprehensive understanding of the acceptance and effectiveness of AIED in self-directed learning. Integrating the TAM with psychological factors is essential to assess the balance between technological support and student learning autonomy, particularly in the context of higher education, which demands continuous independent learning and problem-solving skills (Merino-Campos, 2025; Zhao et al., 2025).

AI tools such as ChatGPT, Gemini, and DeepSeek have been shown to support self-directed learning through adaptive and personalized systems (Ardana et al., 2025; Aulia & Purmadi, 2025). Research on AI in higher education remains predominantly focused on its technical aspects and technology adoption. Studies that explicitly link AI usage to pedagogical learning outcomes, such as learning autonomy and effectiveness, are still relatively limited (Zawacki-Richter et al., 2019). Furthermore, a research gap exists in the specific context of engineering students. Most previous studies have not comprehensively examined the impact of AI on the effectiveness of practical learning and application-oriented needs that characterize engineering education (Fan et al., 2025). Research on AI in higher education also tends to be conducted in theoretical or general learning contexts, while the application of AI in practice-based learning and engineering disciplines remains limited and requires further investigation (Crompton and Burke, 2023).

This study focuses on analyzing the impact of AIED on learning effectiveness and learning autonomy among engineering students by employing a modified TAM framework. The novelty of this study lies in the integration of AIED into practice-based engineering education and the extension of the theoretical framework to assess the balance between technological support and student learning autonomy (J. Wang et al., 2025). Theoretically, this study is important because it provides new insights into how AIED influences the effectiveness and learning autonomy of engineering students who are oriented toward practical and field-based learning (Fan et al., 2025). It also enriches knowledge on the integration of AI into adaptive learning systems in higher education (J. Wang et al., 2025). Practically, this study contributes to the development of AIED-based learning strategies that are more aligned with the needs of engineering students and industry demand (Baltà-Salvador et al., 2025). This study emphasizes the importance of balancing technological support with student learning autonomy (Rabuandika & Pujiriyanto, 2024). Thus, this research not only strengthens the literature on AI-based learning but also provides a foundation for examining the impact of AIED on learning effectiveness and autonomy among engineering students in the digital era.

This study aims to analyze the impact of AIED implementation on learning effectiveness and learning autonomy among engineering students in the digital era, including evaluating the extent to which this technology can support independent practical learning through intelligent systems. In addition, this study examines the balance between the role of technology and individual autonomy and identifies AIED implementation strategies that can enhance learning effectiveness and autonomy sustainably. The results of this study are expected to contribute to improving learning quality and serve as a foundation for developing innovative learning strategies in the era of digitalization. Based on the above background, this study aims to answer the following questions.

RQ1: How does the application of Artificial Intelligence in Education (AIED) affect the effectiveness and independence of engineering students' learning in the digital age?

METHOD

Research Design

This study uses quantitative methods because they can produce objective and measurable data to explain the relationship between variables (Creswell & Creswell, 2022). The research design used is cross-sectional, which is the collection of data at one point in time to describe the actual conditions of respondents without the need for long-term observation (Lee & Kim, 2021). This approach is relevant for analyzing the influence of Perceived Usefulness, Self-Efficacy, and Autonomous Learning on the effectiveness and independence of student learning in the use of Artificial Intelligence in Education (AIED).

Participant

The research participants were active students of the Faculty of Engineering, Makassar State University, who had used Artificial Intelligence technology, such as ChatGPT or Gemini, in their academic activities. The sampling technique used was purposive sampling, with the criteria being (1) active students of the Faculty of Engineering and (2) users of AI in the learning process, reference search, or task completion (Palinkas et al., 2015; Etikan, 2016). Data were collected through an online questionnaire based on Google Forms, which was distributed online and directly on campus.

Instrument

The research instrument consisted of two parts: demographic data and research variable statements. The research variables included Perceived Usefulness (X1), self-efficacy (X2), Willingness for

Autonomous Learning (X3), and Learning Effectiveness and Autonomy (Y). Each variable was measured using five indicators based on a 1–5 Likert scale, ranging from "strongly disagree" to "strongly agree" (Joshi et al., 2015). Prior to distribution, the instrument was validated through consultation with expert lecturers to ensure the suitability of the indicators with the constructs being measured.

Table 1. Research Instruments

No	Variable	Indicator	Instrument	Statement	References
1.	Perceived Usefulness (Students perception of the usefulness of Artificial Intelligence (AI)	Improving learning efficiency with the help of Artificial Intelligence (AI) Belief in the effectiveness of Artificial Intelligence (AI) The role of Artificial Intelligence (AI) in achieving learning objectives Artificial Intelligence (AI) support for deep understanding Artificial Intelligence (AI) support for deep understanding	I believe that the use of Artificial Intelligence (AI) technology can improve efficiency in my learning process. I believe that the use of Artificial Intelligence (AI) has had a positive impact on improving my learning outcomes. I believe that the use of Artificial Intelligence (AI) technology can improve the effectiveness of my learning process. I believe that artificial intelligence will help me achieve my learning goals more effectively. I feel that the application of Artificial Intelligence (AI) technology supports my understanding of the material in a more profound and meaningful way.	(1-5)	(L. Wang & Li, 2024)
2.	Self-Efficacy (The level of students' confidence in using Artificial Intelligence (AI))	The ability to use Artificial Intelligence (AI) for learning Confidence in learning new skills based on Artificial Intelligence (AI) Adaptation to developments in Artificial Intelligence (AI) technology Utilization of Artificial Intelligence (AI) according to learning needs Resilience in facing the challenges of using Artificial Intelligence (AI)	I feel capable of using Artificial Intelligence (AI) technology to obtain and manage the information I need for learning. I am confident that I can learn new skills related to the use of Artificial Intelligence (AI), even in fields that I have not mastered before. I am optimistic that I can adapt to developments in Artificial Intelligence (AI) technology and utilize it in completing various academic tasks. I believe that I can adapt and utilize Artificial Intelligence (AI) technology according to my own needs and learning style. I am confident that I can overcome any obstacles or difficulties that arise when using Artificial Intelligence (AI) technology in my learning process.	(6–10)	(L. Wang & Li, 2024)
3.	(Willingness for Autonomous Learning)	Openness to technological innovation in	I am willing and open to utilizing Artificial Intelligence (AI) technology to support my independent learning process.	(11–15)	(L. Wang & Li, 2024)

	Students' willingness and independence in learning using Artificial Intelligence (AI)	independent learning	After using Artificial Intelligence (AI), I became more focused and able to plan my learning activities independently.		
		Independent learning planning through Artificial Intelligence (AI)	The use of artificial intelligence encourages me to actively seek and learn new knowledge independently.		
		Initiative to seek new knowledge Motivation and direction of learning after the use of Artificial Intelligence (AI)	After using Artificial Intelligence (AI), I feel more motivated and have a clearer direction in my learning activities.		
		Independence in managing the learning process based on Artificial Intelligence (AI)	I am confident that I can manage and control my own learning process with the help of Artificial Intelligence (AI) technology.		
4.	(Learning Effectiveness and Autonomy) The level of learning effectiveness and autonomy of students in Artificial Intelligence (AI)-based learning.	Effectiveness of material comprehension through Artificial Intelligence (AI)	Artificial Intelligence (AI)-based learning helps me understand the material more quickly and clearly.	(16–20)	(Sutrisno et al., 2023)
		Independence in managing AI-based learning strategies and time	I can manage my own study time and strategy with the help of Artificial Intelligence (AI).		
		Utilization of Artificial Intelligence (AI) features to improve learning outcomes	The Artificial Intelligence (AI) feature helps me improve my learning outcomes.		
		Strategies for independent learning with Artificial Intelligence (AI)	I use Artificial Intelligence (AI) technology to help manage my study time and strategy so that my learning process becomes more effective and independent.		
		Artificial Intelligence (AI) feedback on independent learning	Artificial Intelligence (AI)-based learning provides feedback and recommendations that help me improve my results and increase my learning independence.		

Procedure

The research procedure consisted of four stages: (1) developing instruments based on Google Forms; (2) content validation by experts; (3) distributing questionnaires to engineering students who met the criteria; and (4) collecting and verifying data before analysis. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS because this method supports complex predictive models with relatively small sample sizes and does not require normal distribution (Latan & Noonan, 2017).

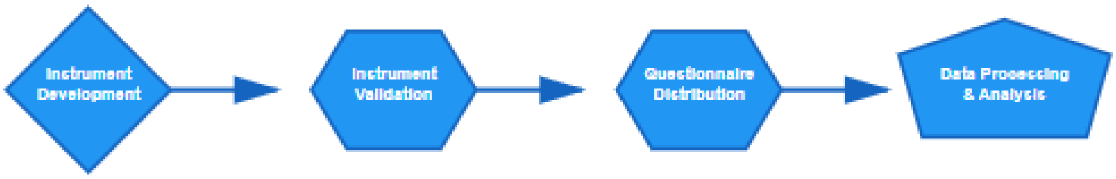

Figure 1. Research Procedure

Data Analysis

Model evaluation was conducted using outer and inner models. The outer model was used to test the reliability and validity of the construct through outer loading indicators ≥ 0.70, Cronbach's Alpha ≥ 0.70, Composite Reliability ≥ 0.70, AVE ≥ 0.50, and HTMT ≤ 0.90 as a measure of discriminant validity (Henseler et al., 2015; Kock, 2015). The inner model was used to test the relationship between variables using the 5,000 resample bootstrapping technique, with a t-statistic value of > 1.96 at α = 0.05 as the significance threshold.

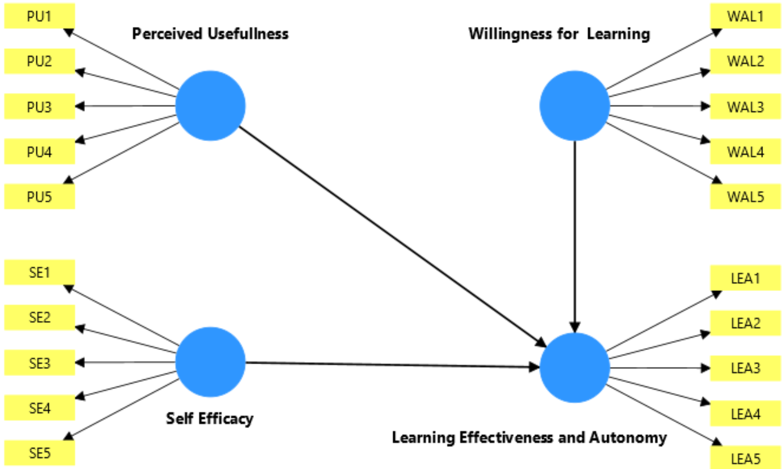

Figure 2. The Model Proposed in This Study

Hypothesis:

H1: Perceived Usefulness has a significant positive effect on Learning Effectiveness and Autonomy.
H2: Self-efficacy has a significant positive effect on Learning Effectiveness and Autonomy.
H3: Willingness to learn autonomously has a significant positive effect on learning effectiveness and autonomy.

RESULTS AND DISCUSSION

Respondent Demographic Analysis

This section describes the demographic profiles of the respondents participating in the study. The total sample size for this study consisted of 90 respondents. The demographic information of the respondents is summarized in the table below, which includes gender, age, semester, faculty, class year, and experience in using artificial intelligence (AI).

Table 2. Respondent Demographic Data

No	Category	Description	Percentage
1.	Gender	Male	32.2%
		Female	67.8%
2.	Age	17	2.2%
		18	24.4%
		19	48.9%

		20	23.3%
		21	1.1%
3.	Semester	I	23.3%
		III	75.6%
		V	1.1%
		VII	0.0%
4.	Faculty of Engineering	Yes	100.0%
		No	0.0%
5.	Generation	2023	1.1%
		2024	74.4%
		2025	24.4%
6.	Are you a student at the Faculty of Engineering, University of Makassar who has used AI (CHAT GPT, COPILOT, etc.)?	Yes	100.0%
		No	0.0%

Source: Processed data, 2025

The description of the respondents in the table shows clear and focused characteristics. Demographically, the group of participants was dominated by one gender and was in an age range that reflected the active student population, especially those in the early to middle stages of their studies. The semester distribution also shows a tendency for most respondents to be at a stage of study where they have begun to enter the core academic material, while only a few are in their early semesters or nearing the end of their studies. The scope of the faculty shows that the respondents were from an engineering background, so the data obtained are relevant to the context of research focusing on engineering students. The composition of the cohorts shows a dominance of newer cohorts, illustrating that new and second-year students were more active in responding than older cohorts.

One important finding was the use of artificial intelligence technology, where all respondents had experience using AI platforms. This shows that technologies such as AI are already deeply embedded in the academic lives of engineering students, both as learning aids and as part of other academic requirements. Overall, these characteristics provide a strong indication that the respondent population is a group that is familiar with technology, is at an active stage of academic development, and is representative of the research context related to learning and perceptions of technology in an engineering environment.

Inner Model

Convergent Validity and Construct Reliability

Table 3 presents the results of the evaluation of convergent validity and construct reliability in the PLS-SEM model, which includes four latent constructs: PU, Self-Efficacy, Willingness Autonomous for Learning, and Learning Effectiveness and A. Each construct was measured using several indicators analyzed based on outer loadings, Cronbach's alpha, rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE). In general, the outer loading values for all indicators ranged from 0.766 to 0.952, illustrating the strong contribution of the indicators to the constructs they represent.

Table 3. Results of Convergent Validity and Construct Reliability Evaluation

Construction	item	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Usefullness	PU1	0,766	0,901	0,904	0,927	0,718
	PU2	0,866				
	PU3	0,883				
	PU4	0,852				
	PU5	0,866				
Self Efficacy	SE1	0,878	0,913	0,922	0,935	0,741
	SE2	0,825				

	SE3	0,902				
	SE4	0,845				
	SE5	0,853				
Willingness Autonomous for Learning	WAL1	0,891	0,905	0,907	0,930	0,726
	WAL2	0,823				
	WAL3	0,838				
	WAL4	0,852				
	WAL5	0,853				
Learning Effectiveness and Autonomy	LEA1	0,792	0,874	0,876	0,909	0,666
	LEA2	0,888				
	LEA3	0,788				
	LEA4	0,816				
	LEA5	0,792				

Source: Processed data, 2025

The table illustrates the measurement quality of each variable in the study through convergent validity and reliability tests. Overall, all the constructs showed good performance based on the displayed values. Each indicator in each variable contributes strongly to its construct, as indicated by the adequate and consistent loading values. The reliability of each variable was also very good, as reflected in the high internal consistency. The reliability test values showed that the items comprising each construct had stable and reliable relationships. In addition, the ability of each variable to explain the variance of its indicators also meets the standard criteria, which means that each construct has a strong representation of the concept being measured. In summary, the table shows that all constructs in the study have valid and reliable instrument quality, so they can be used with confidence for further analyses.

Discriminant Validity

Table 4 presents the results of the discriminant validity test using the Fornell-Larcker criterion in the PLS-SEM model. This table includes four latent constructs that were tested: learning effectiveness and autonomy, perceived usefulness, self-efficacy, and willingness to learn autonomously. In this table, the Average Variance Extracted (AVE) square root value of each construct is compared with its correlation with other constructs. The analysis results showed that all constructs met the discriminant validity criteria, as indicated by the AVE square root value being higher than the correlation value between constructs.

Table 4. Results of the Fornell-Lacker Validity Test

	Learning Effectiveness and Autonomy	Perceived Usefulness	Self Efficacy	Willingness Autonomous for Learning
LEA	**0.720**			
PU	0.820	**0.847**		
SE	0.792	0.739	**0.861**	
WAL	0.849	0.800	0.811	**0.852**

Source: Processed data, 2025

The table presents the results of discriminant validity testing using the Fornell–Larcker criterion. The results show that each construct in the model can distinguish itself well from the other constructs. The AVE root values for each variable are higher than their correlations with other variables; therefore, each construct is considered to have conceptual uniqueness, and there is no overlap between variables. Overall, the measurement model met discriminant validity and could be used in the next stage of the analysis. These findings indicate that the relationships between the

variables are within reasonable limits and do not dominate each other. Thus, each construct can provide specific information to explain the phenomenon under study. This condition confirms that the instruments used were able to accurately capture the characteristics of the concepts without blurring the definitional boundaries.
In addition, these results indicate that the constructed theoretical model is consistent with the obtained data structure. The variables involved show harmony between the theoretical concepts and measurement results, thereby strengthening the reliability and credibility of the research findings. Discriminant validity is an important foundation before testing the structural relationships in the next model.

Outer Model

Table 5 presents the results of the hypothesis testing conducted through PLS-SEM analysis, which provides an overview of the relationships between latent constructs based on path coefficient values, T-statistics, p-values, and final decisions regarding the significance of these relationships. The results of the analysis show that all hypotheses in this research model are positive and significant, so that the three relationships between variables can be said to be empirically supported

Table 5. Results of the Hypothesis Testing Between Latent Constructs

	Hypothesis	Path Coef	T Statistics	P Values	Decision
H1	PU -> LEA	0.240	1,961	0,025	Positive and Significant
H2	SE -> LEA	0.279	2,792	0,003	Positive and Significant
H3	WAL -> LEA	0.483	3,500	0,000	Positive and Significant

Source: Processed data, 2025

The table presents the results of the analysis of the relationships between the latent variables in the structural model. Each hypothesis showed a positive direction of influence and was at an acceptable level of significance; therefore, all hypotheses were supported by the data. This confirms that each independent variable plays a role in influencing the dependent variable. The findings show that perceived usefulness, self-confidence, and willingness to learn independently contribute to increased learning effectiveness and autonomy. These three variables have been proven to provide a unidirectional boost to strengthen individual learning abilities. In addition, the strength of the relationship indicated by the statistical values suggests that the structural model is in good and consistent condition. The overall results support the notion that the variables tested are important predictors that can significantly explain the variation in the outcome construct.

Discussion

The analysis of the research results shows that all predictor variables contribute positively to the effectiveness and autonomy of students learning (LEA). The first hypothesis shows that Perceived Usefulness has a positive and significant effect on Learning Effectiveness and Autonomy. This means that the more students feel the benefits of using AI (e.g., ease of understanding material, time efficiency, and practicality of features), the more effective and independent they are in their learning process. A T-statistic value greater than 1.96 and a p-value < 0.05 confirmed that this relationship was empirically proven. These results are consistent with the research by, which states that the perceived benefits of digital technology can improve the quality of the learning process and encourage independent student engagement. Similar findings were reported by Al-Qaysi et al. (2020), who confirmed that perceived usefulness is a major factor influencing the success of technology-based learning.
The second hypothesis proves that self-efficacy has a positive and significant effect on learning effectiveness and autonomy in this study. Students with high self-confidence in using AI will be more confident in exploring material, making learning decisions, and completing tasks without relying heavily on others. A p-value well below 0.05 indicates a strong and highly significant effect. Zhao et

al. (2025) support these results by stating that self-efficacy is a strong predictor of student independence and engagement in digital learning. In addition, Putri et al.(2025) found that the higher the self-efficacy, the more independent and effective students are in the online learning process.

The third hypothesis showed the greatest effect compared to the other hypotheses. Willingness to learn autonomously proved to be very significant in increasing Learning Effectiveness and Autonomy. This means that students with a strong willingness to learn independently using AI (e.g., learning initiative, internal motivation, and readiness to manage learning strategies) will achieve better and more independent learning outcomes. The path coefficient of 0.483 indicates a strong relationship, and the p-value of 0.000 indicates a very high significance. These findings are in line with Sutrisno et al. (2023), who confirmed that the use of AI can facilitate intrinsic motivation and increase students' learning autonomy. Ramdhani and Hakiman (2025) also proved that students willing to learn independently through AI showed a significant increase in learning effectiveness and independence.

Structural model analysis shows that willingness to learn autonomously (WAL) is the strongest predictor of Learning Effectiveness and Autonomy (LEA), surpassing the influence of Perceived Usefulness and Self-Efficacy. The strength of WAL as a predictor underscores that students' internal motivation and willingness to take responsibility for their own learning are key factors determining their success in utilizing Artificial Intelligence in Education (AIED). Students with high WAL proactively use AI in their SRL cycle (planning, performance, and self-reflection) as a self-managed strategic tool rather than as a source of dependence.

The findings of this study provide important theoretical implications for the field of Artificial Intelligence in Education (AIED), particularly in understanding the role of motivational factors in technology-supported learning. The results demonstrate that willingness to learn autonomously is the strongest predictor of Learning Effectiveness and Autonomy, surpassing perceived usefulness and self-efficacy. This highlights that students' internal motivation and readiness to take responsibility for their own learning play a more critical role than technological perception alone. Consequently, this study reinforces the self-regulated learning theory by positioning learning autonomy as the central mechanism through which AI enhances learning outcomes.

From a practical perspective, the results suggest that higher education institutions should move beyond emphasizing access to AI tools and focus on fostering students' autonomous learning capabilities. Educational practices should integrate AI in ways that encourage initiative, independent problem solving, and strategic learning behaviors. Lecturers and curriculum designers are encouraged to design learning activities that position AI as a supportive learning partner rather than a substitute for student effort, thereby maximizing the effectiveness of AI integration in engineering education.

This study makes an important contribution by strengthening and expanding the Technology Acceptance Model (TAM) through the integration of the variables of Self-Efficacy and Willingness for Autonomous Learning, which have been proven to have a significant influence on the effectiveness and independence of student learning in the context of AIED. Empirically, this study presents the latest findings on engineering students, who are rarely studied specifically, thus providing a more comprehensive picture of psychological readiness and independent learning behavior in technology-based educational environments. Practically, this study also provides recommendations that can be used by educational institutions to design more adaptive, effective, and student-independent learning strategies and policies on the use of AI. The results of this study provide an important foundation for further studies to understand how various internal and external factors influence the successful implementation of AI in higher-education institutions.

Despite providing meaningful findings, this study had several limitations. First, the research sample was limited to students from the Faculty of Engineering at a single university, which restricts the generalizability of the results to other faculties or higher education institutions. Second, the majority of respondents were drawn from early cohorts and mid-level semesters, who may possess higher levels of technological adaptability than senior students. This imbalance may have influenced students perceptions and the intensity of AI usage in the learning process. Third, this study employed a cross-sectional design, which limits its ability to capture longitudinal changes in students' attitudes, motivation, and effectiveness over time.

Based on these limitations, several recommendations can be made for future research. Subsequent studies should broaden the scope of respondents by involving students from diverse faculties, educational levels, or institutions to enhance the model's external validity. In addition, longitudinal research designs are strongly recommended to examine how AI usage and learning autonomy evolve over time. Future researchers may also incorporate additional variables, such as digital literacy, learning strategies, ethical awareness of AI use, or AI dependency behavior, to obtain a more comprehensive understanding of this phenomenon. Furthermore, the adoption of mixed-methods approaches, such as interviews or analysis of AI usage logs, may provide deeper insights into how students actually utilize AI in their self-regulated learning cycles.

CONCLUSION

This study demonstrates that the application of Artificial Intelligence in Education (AIED) significantly enhances the learning effectiveness and autonomy of engineering students. All hypotheses were confirmed, with Perceived Usefulness showing a positive effect (coefficient = 0.240, T = 1.961, p = 0.025), Self-Efficacy contributing significantly (coefficient = 0.279, T = 2.792, p = 0.003), and Autonomous Learning emerging as the strongest predictor (coefficient = 0.483, T = 3.500, p = 0.000). These findings indicate that students' perceived usefulness of AI, confidence in using it, and willingness to learn independently play crucial roles in improving learning outcomes. The results extend the Technology Acceptance Model (TAM) by validating WAL as a key predictor aligned with Self-Regulated Learning (SRL), suggesting that autonomy is essential in AIED-based environments. However, this study has several limitations, including the use of a cross-sectional design, a sample restricted to engineering students, and reliance on self-reported perceptions, which may limit its generalizability and accuracy. Additionally, this study does not distinguish between different types of AIED tools and excludes other potentially influential variables, such as AI usage intensity and digital literacy. Therefore, future research should employ longitudinal methods, include more diverse student populations across faculties, and incorporate behavioral data, such as system usage logs, to obtain more robust insights. It is also recommended to test different categories of AIED applications through experimental designs and expand the theoretical model by integrating AI-specific factors such as trust, transparency, and quality of interaction, enabling a more comprehensive understanding of AI-based learning effectiveness.

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AUTHOR CONTRIBUTION STATEMENT

HA conceptualized the study, developed the research framework, and drafted the manuscript. IA contributed to instrument development, data collection, data preprocessing, and statistical analysis using partial least squares structural equation modeling. NA provided theoretical guidance, validated the methodology, and supported interpretation of findings. All authors reviewed, revised, and approved the final manuscript and agreed to be accountable for all aspects of the work.

AI DISCLOSURE STATEMENT

The authors declare that generative AI tools were used solely to support language editing, clarity, and readability during manuscript preparation. AI tools were not used in the research design, theoretical development, data collection, statistical analysis, interpretation of results, or formulation of conclusions. All AI-assisted content was critically reviewed by the authors, who take full responsibility for the accuracy, originality, and integrity of the manuscript.

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