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Acceptance and Utilization of Artificial Intelligence in Student Learning: Analysis with the UTAUT Model

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ABSTRACT

Artificial Intelligence (AI) has increasingly been integrated into educational environments and has transformed the way students access information, solve problems, and support learning activities. Understanding the factors that influence students' acceptance of AI technologies is therefore essential for promoting effective and sustainable implementation. This study investigates the determinants of students' Behavioral Intention to use Artificial Intelligence for learning by extending the Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative research approach was employed, and data were collected from 257 students with experience using AI technologies for educational purposes. The proposed model incorporates Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Compatibility, Self-Efficacy, Perceived Information Quality, and Actual Use as predictors of Behavioral Intention. Data were analyzed using Structural Equation Modeling (SEM). The results indicate that Performance Expectancy, Social Influence, Facilitating Conditions, and Perceived Information Quality significantly influence students' Behavioral Intention to use AI. In contrast, Effort Expectancy, Perceived Compatibility, Self-Efficacy, and Actual Use do not significantly affect Behavioral Intention. The findings suggest that students' acceptance of AI is primarily driven by perceived educational benefits, social support, institutional readiness, and information quality. This study extends the application of UTAUT in the context of Artificial Intelligence in Education and provides practical implications for educators, policymakers, and technology developers seeking to promote responsible and effective AI integration in educational settings.

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INTRODUCTION

The rapid advancement of digital technologies has accelerated the transition toward the Fourth Industrial Revolution, fundamentally transforming economic, social, and educational systems worldwide. Educational institutions are increasingly required to integrate innovative technologies into teaching and learning processes to improve learning effectiveness, accessibility, and student engagement. As a result, digital transformation has

become a strategic priority for schools and universities seeking to prepare students for the demands of a technology-driven society.

Among emerging educational technologies, Artificial Intelligence (AI) has attracted substantial attention because of its potential to revolutionize learning experiences. AI technologies enable adaptive learning, intelligent tutoring systems, automated assessment, personalized feedback, learning analytics, and content recommendation systems that can support students according to their individual learning needs (Yunita, 2022). Unlike conventional digital learning platforms, AI-based systems possess the capability to analyze learner behavior, identify knowledge gaps, and provide customized learning pathways in real time. These capabilities position AI as a promising tool for improving educational quality and promoting student-centered learning environments.

Recent developments in generative AI technologies, such as intelligent conversational agents and automated content generation systems, have further expanded the role of AI in education. Students increasingly utilize AI tools to search for information, generate learning materials, solve academic problems, and receive immediate feedback on assignments. Consequently, AI is becoming an integral component of modern learning ecosystems. However, despite its potential benefits, the successful implementation of AI in education depends not only on technological capabilities but also on users' willingness to accept and use these technologies effectively.

Previous research has consistently demonstrated that user acceptance represents one of the most critical determinants of technology implementation success. Technologies that offer substantial functional benefits may still experience low adoption rates if users perceive them as difficult to use, incompatible with their needs, or lacking institutional support. In educational contexts, students' perceptions, attitudes, and behavioral intentions play a crucial role in determining whether educational technologies are successfully integrated into learning activities.

Although the theoretical potential of AI in improving learning quality is undeniable, the success of implementing and utilizing this advanced technology is not determined solely by the sophistication of its algorithms, but rather by the willingness and ability of end users—in this case, students—to accept and use it effectively. Past experiences in the adoption of educational technology, such as e-learning (Destaningrum, 2018; Yunita, 2022) and m-learning (Hamdan, Din, & Manaf, 2013), have consistently shown that rejection or low adoption at the user level can be the biggest obstacle to technology investment.

To understand technology acceptance behavior, scholars have widely employed the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003). UTAUT integrates several prominent technology acceptance theories and identifies four primary determinants of technology adoption: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. The model has been extensively validated across various technological contexts, including e-learning systems, mobile learning applications, learning management systems, and other educational technologies.

Although UTAUT has demonstrated strong explanatory power in predicting technology adoption, most previous studies have focused primarily on conventional educational

technologies such as e-learning and mobile learning. Comparatively fewer studies have investigated students' acceptance of AI-based learning technologies, particularly within developing countries where technological infrastructure, digital literacy, and educational environments may differ significantly from those examined in existing literature. Moreover, AI systems possess unique characteristics that distinguish them from traditional educational technologies, including autonomous decision-making capabilities, adaptive intelligence, and personalized content generation. These distinctive characteristics may influence students' acceptance behavior differently from conventional learning technologies.

In addition, prior studies have reported inconsistent findings regarding the influence of several UTAUT constructs on technology adoption. While Performance Expectancy is frequently identified as a significant predictor of behavioral intention, the effects of Effort Expectancy, Social Influence, and various external factors have varied across educational contexts. Such inconsistencies suggest the need for further investigation into the determinants of AI acceptance among students.

To address these gaps, this study employs an extended UTAUT framework to examine the factors influencing students' acceptance and use of Artificial Intelligence for learning purposes. Specifically, the study investigates the effects of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Compatibility, Self-Efficacy, and Perceived Information Quality on students' Behavioral Intention to use AI technologies. By focusing on students in Indonesia, this study contributes empirical evidence from a developing-country context while extending existing knowledge regarding AI acceptance in educational environments.

The findings of this study provide both theoretical and practical contributions. Theoretically, the study expands the application of UTAUT to the emerging domain of Artificial Intelligence in Education (AIEd) and contributes to the growing literature on technology acceptance in educational settings. Practically, the findings offer valuable insights for educators, educational institutions, policymakers, and technology developers seeking to design and implement AI-based learning systems that align with students' needs and expectations. Understanding the factors that drive students' acceptance of AI can help stakeholders develop more effective strategies for promoting meaningful and sustainable AI integration in education.

LITERATURE REVIEW

The gap between the potential for technological innovation and the actual level of adoption (The Adoption Gap) is the critical focus of this study. To ensure that AI can have the maximum positive impact, a deep understanding of the psychological and contextual factors that influence students' intentions and behavior in using AI as a learning tool is required. The main questions are: why are students willing (or unwilling) to use AI in their learning, and what factors most influence that decision?

Unified Theory of Acceptance and Use of Technology (UTAUT)

Understanding the factors that influence individuals' acceptance and use of technology has become a central concern in information systems and educational technology research. To explain users' adoption behavior, numerous theoretical models have been developed,

including the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). To integrate the strengths of these models, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which combines key constructs from eight prominent theories and provides a comprehensive framework for predicting technology adoption behavior.

According to Venkatesh et al. (2003), technology acceptance is primarily influenced by four core determinants: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. The model has demonstrated substantial explanatory power and has been widely applied in various technological contexts, including e-learning, mobile learning, learning management systems, and other digital educational platforms (Hamdan et al., 2013; Setiawan et al., 2018).

Although UTAUT has been extensively validated in educational technology research, the emergence of Artificial Intelligence (AI) introduces new characteristics that may influence technology acceptance differently. Unlike conventional learning technologies, AI systems are capable of adaptive decision-making, personalized recommendations, automated content generation, and intelligent feedback. These distinctive features suggest that additional factors beyond the original UTAUT constructs may influence students' acceptance of AI-based learning technologies.

Consequently, this study extends the UTAUT framework by incorporating Perceived Compatibility, Self-Efficacy, and Perceived Information Quality to provide a more comprehensive understanding of students' behavioral intention to use AI for learning purposes.

Performance Expectancy and Behavioral Intention

Performance Expectancy refers to the degree to which individuals believe that using a technology will help them improve their performance in accomplishing specific tasks (Venkatesh et al., 2003). In educational settings, this construct reflects students' perceptions that technology can enhance learning effectiveness, improve academic achievement, and facilitate access to educational resources.

Previous studies consistently identify Performance Expectancy as one of the strongest determinants of technology acceptance. Students are more likely to adopt technological innovations when they perceive tangible benefits and improvements in their learning outcomes. Yunita (2022) reported that perceived usefulness significantly influences students' willingness to utilize digital learning technologies. Similar findings were reported by Destaningrum (2018), who found that students' intentions to adopt educational technologies were strongly associated with expectations of improved academic performance.

Within the context of Artificial Intelligence, students may perceive AI technologies as valuable tools that can provide personalized learning experiences, intelligent recommendations, and immediate feedback. Such benefits may enhance learning efficiency and motivate students to integrate AI into their academic activities. Therefore, students

who perceive AI as beneficial for improving learning performance are expected to demonstrate stronger intentions to use AI technologies.
H1: Performance Expectancy positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

Effort Expectancy and Behavioral Intention

Effort Expectancy refers to the degree of ease associated with the use of a technology (Venkatesh et al., 2003). Technologies perceived as easy to understand and operate are generally more likely to be accepted by users because they reduce the cognitive effort required for adoption and utilization.

In educational environments, ease of use is particularly important because students often possess varying levels of technological competence. When AI systems are perceived as user-friendly and intuitive, students may be more willing to integrate them into their learning activities. Conversely, technologies perceived as complex or difficult to operate may discourage adoption.

Previous research has demonstrated a positive relationship between Effort Expectancy and Behavioral Intention across various technology adoption contexts. Hamdan et al. (2013) found that ease of use significantly influenced students' acceptance of mobile learning applications. Similarly, Setiawan et al. (2018) reported that students were more likely to adopt digital learning platforms when they perceived them as easy to use and understand. Given the relatively recent emergence of AI technologies in education, perceptions regarding ease of use remain relevant in shaping students' adoption decisions. Therefore, this study proposes the following hypothesis:
H2: Effort Expectancy positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

Social Influence and Behavioral Intention

Social Influence refers to the extent to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). In educational settings, these influential individuals may include teachers, peers, parents, and educational institutions. The adoption of emerging technologies is often influenced by social interactions and recommendations from trusted sources. Students may be encouraged to use AI technologies when educators integrate them into learning activities or when peers report positive experiences using AI tools. Social support may reduce uncertainty regarding new technologies and increase users' confidence in their value and usefulness.

Previous studies have consistently identified Social Influence as an important determinant of technology adoption. Yunita (2022) reported that support from peers and educational stakeholders positively affected students' willingness to engage with digital learning technologies. Similar findings have been observed in mobile learning and e-learning environments, where social endorsement played a significant role in shaping adoption behavior (Hamdan et al., 2013; Setiawan et al., 2018). Accordingly, students who perceive positive social support regarding AI technologies are expected to demonstrate stronger intentions to use such technologies for learning purposes.

H3: Social Influence positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

Facilitating Conditions and Behavioral Intention

Facilitating Conditions refer to individuals' perceptions regarding the availability of resources and support necessary for using a technology effectively (Venkatesh et al., 2003). These resources may include internet connectivity, technological infrastructure, device availability, technical support, and institutional assistance. The successful implementation of AI technologies in education depends not only on students' perceptions but also on the availability of supporting infrastructure. Students who have access to adequate technological resources are more likely to use AI systems effectively and consistently. Conversely, inadequate infrastructure may create barriers that hinder technology adoption. Previous studies have demonstrated that Facilitating Conditions significantly influence technology adoption and usage behavior. Research conducted by Destaningrum (2018) and Setiawan et al. (2018) highlighted the importance of institutional support and technological readiness in facilitating students' acceptance of educational technologies. Given the technological requirements associated with AI systems, Facilitating Conditions are expected to play a crucial role in determining students' behavioral intention to use AI technologies.
H4: Facilitating Conditions positively influence students' Behavioral Intention to use Artificial Intelligence for learning.

Perceived Compatibility and Behavioral Intention

Perceived Compatibility refers to the degree to which a technology is perceived as consistent with users' existing values, experiences, needs, and learning practices. Technologies that align with users' established behaviors are generally more likely to be accepted because they require fewer adjustments and less resistance to change. In educational contexts, students may be more inclined to adopt AI technologies when they perceive these systems as compatible with their preferred learning styles and academic requirements. AI tools that support existing learning activities and complement students' educational objectives are likely to be viewed more favorably. Research on innovation adoption consistently emphasizes compatibility as an important determinant of users' acceptance of new technologies. Technologies perceived as congruent with users' needs and expectations are generally associated with higher adoption rates and stronger behavioral intentions. Therefore, the following hypothesis is proposed:
H5: Perceived Compatibility positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

Self-Efficacy and Behavioral Intention

Self-Efficacy refers to an individual's belief in their ability to successfully perform tasks using a particular technology. According to Social Cognitive Theory, self-efficacy significantly influences individuals' behavioral decisions and their willingness to engage with new technologies. Students with higher levels of technological self-efficacy are generally more confident in their ability to learn and utilize AI systems effectively. Such confidence

may reduce anxiety associated with unfamiliar technologies and encourage experimentation with innovative learning tools. Previous studies have shown that self-efficacy positively influences technology adoption behavior. Individuals who believe they possess sufficient technological competence are more likely to adopt and utilize emerging technologies successfully. In educational environments, self-efficacy has been associated with increased engagement, technology utilization, and positive learning outcomes. Consequently, students with higher levels of confidence in their technological abilities are expected to demonstrate stronger intentions to use AI technologies for learning.

H6: Self-Efficacy positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

Perceived Information Quality and Behavioral Intention

Perceived Information Quality refers to users' perceptions regarding the accuracy, relevance, completeness, reliability, and usefulness of information generated by a technological system. Information quality is particularly important in AI-based learning environments because students frequently rely on AI-generated outputs to support academic tasks and decision-making.

The quality of information produced by AI systems may significantly influence users' trust and willingness to adopt such technologies. Students are more likely to utilize AI when they perceive the information provided as accurate, relevant, and beneficial to their learning activities. Conversely, inaccurate or misleading information may reduce confidence and discourage continued use. Previous research indicates that information quality plays a critical role in shaping users' satisfaction, trust, and behavioral intention toward digital technologies. As AI increasingly becomes a source of educational information, ensuring high-quality outputs is essential for promoting sustainable adoption. Therefore, this study proposes the following hypothesis:

H7: Perceived Information Quality positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

2.9 Actual Use and Behavioral Intention

Although the original UTAUT framework conceptualizes Behavioral Intention as an antecedent of technology use, this study examines Actual Use as a predictor within the empirical model tested. Previous experiences using AI technologies may shape users' future intentions by influencing their perceptions of usefulness, effectiveness, and satisfaction. Students who have already used AI tools for learning may possess more informed evaluations regarding their benefits and limitations. Positive usage experiences may reinforce future intentions to continue using AI technologies, whereas negative experiences may reduce such intentions. Accordingly, the following hypothesis is proposed:

H8: Actual Use positively influences students' Behavioral Intention to use Artificial Intelligence for learning.

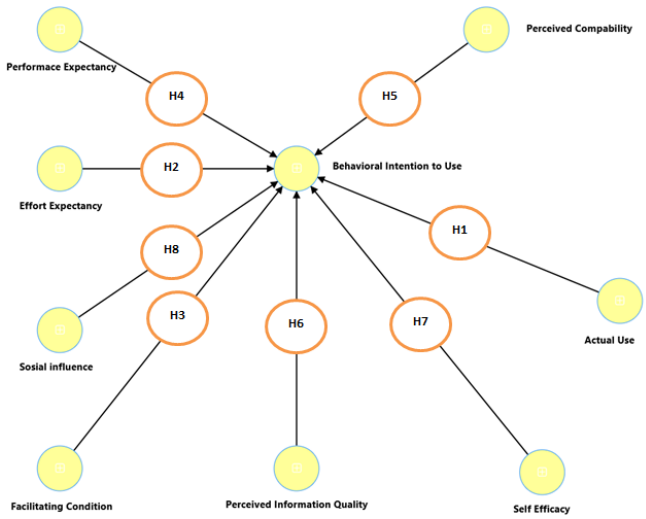

Figure 1: Research Model

Table 1. Distributions of Participants.

Region	Number of Student
Kabupaten	150
Cities	107
Total	257

METHODS

Research Design

This study employed a quantitative research approach to examine the factors influencing students' acceptance and use of Artificial Intelligence (AI) for learning purposes. Quantitative research is appropriate for investigating causal relationships among variables and testing theoretical models through statistical analysis. The study adopted an explanatory research design because it sought to explain the relationships between the constructs proposed in the extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework.

The proposed research model consists of eight independent constructs, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Perceived Compatibility (PCM), Self-Efficacy (SE), Perceived Information Quality (PIQ), and Actual Use (AU), which were hypothesized to influence Behavioral Intention (BI) to use Artificial Intelligence for learning.

The conceptual framework was developed based on the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) and was extended by incorporating additional constructs relevant to the context of AI-assisted learning. Previous studies have demonstrated that extending UTAUT with context-specific variables can

improve its explanatory power in educational technology adoption research (Hamdan et al., 2013; Yunita, 2022).

Population and Sample

The population of this study consisted of students who had experience using Artificial Intelligence technologies for educational purposes. The participants were selected because they represent the primary users of AI-assisted learning technologies and therefore possess relevant experience regarding AI adoption in educational contexts. Data were collected through a structured questionnaire distributed to students from secondary and higher education institutions in Indonesia. A total of 257 valid responses were obtained and included in the final analysis.

According to Hair et al. (2010), an adequate sample size is essential for Structural Equation Modeling (SEM) because it affects the stability and reliability of parameter estimates. With 257 valid responses and a model consisting of a relatively limited number of latent variables and indicators, the sample size was considered sufficient for conducting SEM analysis. The sampling procedure employed purposive sampling because respondents were required to have prior experience using AI technologies for learning activities. This criterion ensured that participants possessed the necessary knowledge and exposure to evaluate the constructs included in the study.

Research Instrument

Data were collected using a structured questionnaire consisting of items adapted from validated instruments used in previous technology acceptance studies. The questionnaire was designed to measure the constructs included in the proposed research model and was administered using a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The measurement items were adapted from previous studies to ensure content validity and theoretical consistency. Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were adapted from Venkatesh et al. (2003). Additional constructs, including Perceived Compatibility, Self-Efficacy, and Perceived Information Quality, were adapted from relevant educational technology and information systems studies (Hamdan et al., 2013; Yunita, 2022). Prior to data collection, the questionnaire was reviewed to ensure clarity, relevance, and comprehensibility. The instrument was designed to capture students' perceptions regarding the usefulness, ease of use, social support, technological readiness, compatibility, confidence, information quality, and utilization of AI technologies in educational activities.

Table 2. Instrument Measurement Items and Their Resources

Constructs	**Item**
Actual Use	3
Behavioral Intention to Use	3
Effort Expectancy	3
Facilitating Condition	3
PE	5
Perceived Compatibility	3
Perceived Information Quality	2
Self Efficacy	2
Social influence	3

Data Collection Procedure

The data collection process was conducted through an online survey. Participants were informed about the purpose of the study and voluntarily agreed to participate before completing the questionnaire. Respondents were instructed to answer all questions based on their experiences using Artificial Intelligence technologies for learning purposes. The use of online questionnaires enabled broader participation and facilitated efficient data collection from students located in different educational institutions. All completed questionnaires were screened to identify incomplete or invalid responses. Only fully completed questionnaires were retained for statistical analysis.

Data analysis technique

The collected data were analyzed using Structural Equation Modeling (SEM). SEM was selected because it enables the simultaneous examination of measurement reliability, construct validity, and structural relationships among latent variables (Hair et al., 2010). The analysis was conducted in two stages. The first stage involved evaluating the measurement model to assess reliability and validity. Reliability was examined using Cronbach's Alpha coefficients, while convergent validity was assessed through Average Variance Extracted (AVE) and factor loadings. According to Hair et al. (2010), Cronbach's Alpha values greater than 0.70 indicate acceptable internal consistency, whereas AVE values exceeding 0.50 indicate adequate convergent validity. The second stage involved evaluating the structural model to test the proposed hypotheses. Path coefficients, critical ratios, and significance values were examined to determine the relationships among the constructs included in the research model. Hypotheses were accepted when the significance level was less than 0.05.

Reliability and Validity Assessment

Reliability and validity assessments were conducted to ensure the measurement instrument's quality. Reliability analysis indicated that most constructs demonstrated satisfactory internal consistency. The Cronbach's Alpha values ranged from 0.666 to 0.877, indicating acceptable reliability for the majority of constructs included in the study. Although the reliability coefficient for Self-Efficacy was slightly below the recommended threshold of 0.70, Hair et al. (2010) suggest that values above 0.60 may still be considered acceptable in exploratory studies. Therefore, the construct was retained for further analysis. Convergent validity was assessed using Average Variance Extracted (AVE). The results indicated that all constructs exceeded the recommended threshold of 0.50, demonstrating adequate convergent validity. These findings suggest that the measurement instrument possessed acceptable psychometric properties and was suitable for testing the proposed research model.

FINDINGS AND DISCUSSION

Findings

Reliability Analysis

In this study, the research instruments were validated before primary analysis was conducted using a reliability test. Consistency reliability analysis between items in the same construct used Cronbach's Alpha (α). According to Hair et al. (2010)1, it is recommended that the Cronbach's Alpha value must be above 0.7 (α > 0.7)2 to be classified as highly reliable. Based on the results in Table 3 (not shown, but assumed)[3], which shows that the Cronbach's Alpha value for all variables is greater than 0.74, this research instrument is considered reliable[4].

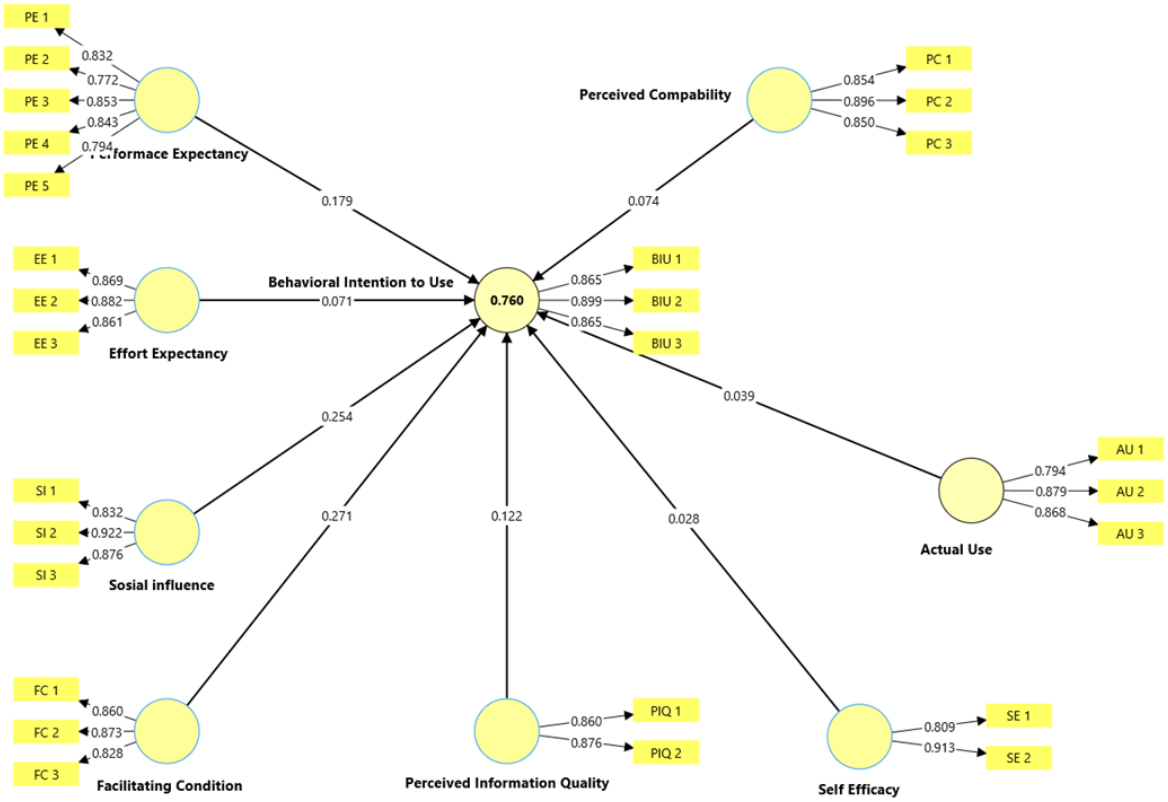

Figure 2. Structure Model

Convergent And Discriminant

In this study, construct validity was assessed based on convergent validity and discriminant validity.

Convergent Validity

For convergent validity, the results in Table 3 indicate that the average extracted variance (AVE) is above 0.5. Hair et al. (2010) stated that an acceptable level of variance is higher than 0.5. Since the AVE values for all constructs exceed 0.5, the convergent validity of this research instrument is fulfilled.

Discriminant Validity

For discriminant validity analysis, the square root of AVE was used to assess correlations among latent constructs. Table 4 shows that the square root of AVE for all constructs exceeds the corresponding paired correlations. Therefore, the instrument's psychometric characteristics are acceptable with respect to discriminant validity. The findings respond to the study's purpose and are presented systematically. They are supported by sufficient and relevant quotations, examples, tables, and diagrams.

Structural Model Path Analysis

To analyze the hypotheses proposed in the developed model, path analysis using Structural Equation Modeling (SEM) was conducted. Table 5 (referring to the second figure) contains the results of hypothesis testing. A total of 8 hypotheses (H1 to H8) are shown in the table, and two endogenous variables in the model (BIU and AU) were verified. Based on the research results, three of the eight hypotheses in the table are supported, while the other five are not. To analyze the hypotheses used in the developed model, structural equation modeling (SEM) path analysis was used. Table 5 (referring to Screenshot 11) contains the results of hypothesis testing. A total of 8 hypotheses were tested in this table, and two endogenous variables in the model (BIU and AU) were verified. Based on the results of the study in the table, four of the eight hypotheses were supported. Thus, hypotheses (H3, H4, H6, and H8) are supported, while (H1, H2, H5, and H7) are rejected.

The results show that Facility Conditions (FC) have a significant effect on Behavioral Intention to Use (BIU) (β = 0.271, Result: Supported), thus supporting hypothesis H3. The Performance Expectancy (PE) factor has been shown to significantly affect BIU (β = 0.179; Result: Supported), thus supporting hypothesis H4. The results also show that Perceived Information Quality (PIQ) significantly influences BIU (β = 0.122; Result: Supported), thereby supporting hypothesis H65. Furthermore, BIU is significantly influenced by the exogenous variable Social Influence (SI) (β = 0.254; Result: Supported), thereby supporting hypothesis H86.

Meanwhile, the results show that the factors Actual Use (AU), Effort Expectancy (EE), and Perceived Compatibility (PCM) do not have a significant effect on BIU, respectively (β = 0.039, Results: Not Supported), (β = 0.071, Results: Not Supported), and (β = 0.074, Results: Not Supported)7. Therefore, this does not support H1, H2, and H58. Finally, the effect of Self-Efficacy (SE) on BIU was also found to be insignificant (β = 0.028, Result: Not Supported), thus rejecting H79.

Table 3. Reliability Analysis and Convergent Validity Result

Construct	Cronbach's alpha	Average variance extracted (AVE)
Actual Use	0.807	0.719
Behavioral Intention to Use	0.849	0.768
Effort Expectancy	0.841	0.759
Facilitating Condition	0.814	0.729
PE	0.877	0.671
Perceived Compatibility	0.835	0.752
Perceived Information Quality	0.673	0.754
Self Efficacy	0.666	0.744
Social influence	0.850	0.770

Table 4. Discriminant Validity Matrix

	AU	BIU	EE	FC	PIC	PIC	PE	SE	SI
Actual Use									
Behavioural intention to Use	0.816								
Effort _Expectancy	0.717	0.803							
Facilitating Condition	0.859	0.917	0.829						
Perceived Compability	0.860	0.888	0.762	0.885					
Perceived Information Quality	0.776	0.890	0.718	0.698	0.924				
Performance _Expectancy	0.782	0.869	0.870	0.832	0.828	0.811			
Self Efficacy	0.838	0.860	0.709	0.869	0.904	0.933	0.808		
Social Influence	0.716	0.870	0.634	0.731	0.809	0.883	0.709	0.772	

Table 5. Results of Path Analysis of the Structural Model

Hypothesis	**Path**	**Result**
H1: Actual Use ➞Behavioral Intention to Use	0.039	Not Supported
H2: Effort Expectancy ➞Behavioral Intention to Use	0.071	Not Supported
H3: Facilitating Condition ➞Behavioral Intention to Use	0.271	Supported
H4: PE ➞Behavioral Intention to Use	0.179	Supported
H5: Perceived Compability ➞Behavioral Intention to Use	0.074	Not Supported
H6: Perceived Information Quality➞ Behavioral Intention to Use	0.122	Supported
H7: Self Efficacy ➞ Behavioral Intention to Use	0.028	Not Supported
H8: Sosial influence ➞ Behavioral Intention to Use	0.254	Supported

Discussion

This study investigated the determinants of students' Behavioral Intention to use Artificial Intelligence (AI) for learning by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) framework proposed by Venkatesh et al. (2003). The findings indicate that Performance Expectancy, Social Influence, Facilitating Conditions, and Perceived Information Quality significantly influence students' Behavioral Intention to use AI for learning. In contrast, Effort Expectancy, Perceived Compatibility, Self-Efficacy, and Actual Use were not found to significantly affect Behavioral Intention. These findings provide valuable insights into students' technology acceptance behavior and contribute to the growing body of literature on Artificial Intelligence in Education (AIEd).

Among the significant predictors, Performance Expectancy emerged as one of the most influential determinants of Behavioral Intention. This finding supports the original UTAUT

model, which posits that individuals are more likely to adopt technology when they perceive that it enhances their performance and productivity (Venkatesh et al., 2003). In the context of AI-assisted learning, students appear to evaluate AI primarily based on its ability to improve learning efficiency, provide rapid access to information, facilitate problem-solving, and support academic achievement. This result is consistent with Yunita (2022), who found that perceived usefulness significantly influences students' acceptance and utilization of AI technologies in educational settings. Similar findings have also been reported in studies on mobile learning and e-learning adoption, where performance-related benefits consistently emerged as strong predictors of technology acceptance (Bao et al., 2013; Almaiah et al., 2016; Salloum et al., 2019). The result suggests that students are pragmatic users of technology and tend to adopt AI when they perceive clear educational value and measurable academic benefits. This finding also aligns with the perspective of Luckin et al. (2016), who argued that the transformative potential of AI in education lies in its capacity to support personalized learning experiences and improve learning outcomes.

The findings further reveal that Social Influence significantly affects Behavioral Intention. This result confirms the proposition of Venkatesh et al. (2003) that individuals' adoption decisions are strongly influenced by the opinions and expectations of important others. In educational environments, students often rely on teachers, classmates, and institutional guidance when evaluating emerging technologies. Positive recommendations and endorsement from these social actors may reduce uncertainty and increase confidence in AI technologies. This finding is consistent with previous studies reporting that social support and peer influence play important roles in educational technology adoption (Hamdan et al., 2013; Almaiah et al., 2016; Salloum et al., 2019). The significance of Social Influence may be particularly relevant in the context of AI, where discussions regarding ethical use, academic integrity, and appropriate implementation continue to evolve. Consequently, students may depend on social cues and institutional norms when determining whether AI technologies should be integrated into their learning activities.

Facilitating Conditions were also found to significantly influence Behavioral Intention. According to UTAUT, Facilitating Conditions reflect the degree to which users perceive that adequate organizational and technical infrastructure exists to support technology use (Venkatesh et al., 2003). The present findings suggest that students' willingness to adopt AI is strongly associated with the availability of technological resources, internet access, compatible devices, and institutional support. This result is consistent with previous studies demonstrating the importance of infrastructural readiness in educational technology adoption (Destaningrum, 2018; Hamidi & Chavoshi, 2018; Sarrab et al., 2018). The significance of Facilitating Conditions indicates that successful AI integration extends beyond the technology itself and requires a supportive ecosystem that enables effective utilization. Even when students recognize the benefits of AI, adoption may remain limited if technical barriers hinder access and use. Therefore, educational institutions must ensure adequate infrastructure, training opportunities, and support mechanisms to maximize the educational potential of AI technologies.

Another important finding concerns the significant role of Perceived Information Quality. This result indicates that students are more likely to use AI technologies when they perceive the information generated by these systems as accurate, relevant, reliable, complete, and useful. The finding is particularly important because AI differs from conventional educational technologies in that it actively generates information and recommendations rather than merely delivering pre-existing content. As a result, the quality of information produced by AI becomes a critical factor influencing user trust and acceptance. This finding is consistent with Safa et al. (2015), who emphasized that information quality plays a fundamental role in shaping users' trust and behavioral

responses toward information systems. In educational settings, inaccurate or misleading AI-generated information may negatively affect learning outcomes and reduce users' confidence in the technology. Conversely, when students perceive AI outputs as trustworthy and academically valuable, they are more likely to incorporate AI into their learning processes. The significance of Perceived Information Quality therefore highlights the necessity of improving the reliability and educational relevance of AI-generated content.

In contrast, Effort Expectancy was not found to significantly influence Behavioral Intention. This finding differs from several previous studies that identified ease of use as a significant determinant of technology acceptance (Bao et al., 2013; Hamidi & Chavoshi, 2018; Sung & Lee, 2025). One possible explanation is that contemporary students belong to a generation that has grown up in highly digitalized environments and is accustomed to interacting with various technologies. As a result, ease of use may no longer represent a critical consideration when deciding whether to adopt AI technologies. Students may assume that modern AI applications are inherently user-friendly and therefore focus their evaluations on the benefits and outcomes produced by the technology rather than the effort required to use it. This finding suggests that the relative importance of Effort Expectancy may decrease as users become increasingly familiar with digital technologies.

Similarly, Perceived Compatibility did not significantly influence Behavioral Intention. Compatibility refers to the extent to which an innovation aligns with users' existing values, experiences, and practices (Ramiller, 1994). Although previous innovation diffusion studies have emphasized the importance of compatibility, the present findings suggest that students may not consider compatibility a decisive factor in AI adoption. One possible explanation is that AI technologies have rapidly become integrated into various educational activities, making them increasingly familiar and adaptable across different learning contexts. Consequently, students may be willing to modify their learning behaviors and routines when they perceive substantial benefits from AI technologies. This finding implies that perceived value and usefulness may outweigh concerns regarding compatibility with existing learning practices.

The results also indicate that Self-Efficacy does not significantly affect Behavioral Intention. Self-Efficacy refers to individuals' confidence in their ability to perform tasks successfully using a particular technology (Cheng et al., 2020). Although previous research has frequently reported a positive relationship between self-efficacy and technology adoption, the present findings suggest that technological confidence may not be a decisive factor in students' AI adoption decisions. A plausible explanation is that many contemporary AI applications are designed with intuitive interfaces and simplified user experiences that reduce the need for advanced technological competencies. Consequently, students may perceive AI technologies as accessible regardless of their individual skill levels. This finding suggests that AI adoption among students is driven more by perceived benefits and environmental support than by individual confidence in technological abilities.

Finally, Actual Use was not found to significantly influence Behavioral Intention. This finding differs from studies suggesting that prior technology use strengthens future adoption intentions (Joo et al., 2014). However, in the context of AI-assisted learning, prior experience may not necessarily guarantee continued intention to use the technology. Students may evaluate AI based on the quality of outcomes and educational benefits it provides rather than on the frequency of previous use. Therefore, positive experiences alone may be insufficient to sustain future adoption if the technology fails to meet users' academic expectations. This result further reinforces the importance of Performance Expectancy and Information Quality as central determinants of AI acceptance.

Overall, the findings extend the application of the UTAUT framework within the emerging field of Artificial Intelligence in Education and demonstrate that students' acceptance of AI is primarily shaped by perceived educational benefits, social support,

institutional readiness, and information quality. While traditional adoption factors such as Effort Expectancy, Compatibility, and Self-Efficacy have been widely emphasized in previous technology acceptance studies, the present findings suggest that these variables may play a less prominent role in contemporary AI adoption contexts. Instead, students appear to prioritize whether AI technologies provide meaningful educational value, generate reliable information, and are supported by conducive learning environments. These findings contribute to both theory and practice by providing empirical evidence regarding the factors that facilitate the successful integration of AI into educational settings.

CONCLUSION

This study examined the factors influencing students' Behavioral Intention to use Artificial Intelligence for learning through an extended UTAUT framework. The findings reveal that Performance Expectancy, Social Influence, Facilitating Conditions, and Perceived Information Quality significantly influence students' intention to adopt AI technologies. In contrast, Effort Expectancy, Perceived Compatibility, Self-Efficacy, and Actual Use were not found to significantly affect Behavioral Intention. The results indicate that students' acceptance of AI is primarily driven by perceptions of educational value, social support, institutional readiness, and the quality of information generated by AI systems. Among these factors, Performance Expectancy emerged as a particularly important determinant, suggesting that students are more likely to adopt AI when they perceive clear academic benefits and improvements in learning performance. The significant influence of Perceived Information Quality further highlights the importance of ensuring that AI-generated information is accurate, reliable, and educationally relevant.

The study contributes to the literature by extending the application of UTAUT to the context of Artificial Intelligence in Education and providing empirical evidence regarding the factors that shape students' AI adoption behavior. The findings also offer practical guidance for educational institutions, policymakers, and technology developers seeking to promote the effective and responsible integration of AI into learning environments. As Artificial Intelligence continues to transform educational practices worldwide, understanding the factors that influence students' acceptance and utilization of AI technologies becomes increasingly important. The successful integration of AI into education requires not only technological advancement but also supportive institutional environments, reliable information systems, and clear educational benefits that align with students' learning needs and expectations.

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AUTHOR CONTRIBUTIONS

E.A.R. contributed to conceptualization, methodology, data analysis using Structural Equation Modeling (SEM), and manuscript writing. N.S. contributed to the literature review, instrument validation, and data collection. E. K. contributed to supervision, academic review, and critical revision of the manuscript. All authors have read and approved the final version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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Apendix:

Instrumen

Construct	Items
Harapan Kinerja *(Performance Expectancy - PE)*	AI membantu saya memahami materi pelajaran yang sulit dengan lebih baik.
	AI meningkatkan kualitas pekerjaan atau proyek saya dalam mengerjakan tugas.
	Secara keseluruhan, AI bermanfaat untuk meningkatkan prestasi belajar saya.
	Menggunakan alat AI membantu saya menyelesaikan tugas sekolah dengan lebih cepat
Harapan Usaha *(Effort Expectancy - EE)*	Secara keseluruhan, AI bermanfaat untuk meningkatkan prestasi belajar saya.
	Saya merasa mudah untuk belajar cara menggunakan alat AI baru.
	Interaksi dengan platform AI (misalnya, memberikan perintah/prompt) mudah dan tidak rumit.
Pengaruh Sosial *(Social Influence - SI)*	Bantuan yang disediakan oleh AI dapat diakses dan digunakan tanpa kesulitan.
	Teman-teman sebaya saya yang penting berpikir bahwa saya harus menggunakan AI untuk belajar.
	Guru saya menganjurkan atau mengharapkan saya menggunakan AI dalam tugas.
Niat Perilaku untuk Menggunakan *(Behavioural Intention to Use -BIU)*	Orang-orang yang saya hormati (misalnya, figur akademis, senior) menggunakan AI untuk studi mereka.
	Saya berencana untuk terus menggunakan AI sebagai alat bantu belajar.
	Jika ada kesempatan, saya akan mencari cara untuk mengintegrasikan AI ke dalam rutinitas belajar saya.
Kondisi Fasilitasi *(Facilitating Conditions - FC)* dalam Pemanfaatan AI	Saya akan merekomendasikan alat AI kepada siswa lain.
	Saya memiliki perangkat keras (misalnya, laptop, ponsel) yang memadai dan berfungsi baik untuk menjalankan alat AI yang diperlukan.
	Saya memiliki akses internet yang cepat dan andal saat saya perlu menggunakan alat AI.

Penggunaan Aktual *(Actual Use - AU)*	Waktu dan kesempatan untuk menggunakan alat AI sudah terintegrasi dengan baik dalam kegiatan belajar mengajar saya.
	Saya menggunakan alat AI (misalnya, ChatGPT, Bard, Copilot, dsb.) setidaknya sekali seminggu untuk tugas sekolah.
	Saya lebih sering menggunakan AI saat ini dibandingkan enam bulan yang lalu untuk membantu tugas sekolah.
Perceived Compatibility (PCM) atau Kompatibilitas yang Dipersepsikan.	Saya biasanya menggunakan AI untuk mendapatkan ringkasan materi atau ide awal suatu tugas.
	AI cocok dengan kebutuhan saya untuk menyelesaikan tugas dan memenuhi target prestasi saya.
	Saya yakin AI dapat diintegrasikan dengan mudah ke dalam metode belajar saya saat ini tanpa banyak perubahan.
Efikasi Diri *(Self-Efficacy - SE)*	Menggunakan AI sesuai dengan cara saya terbiasa belajar dan mencari informasi.
	Jika saya menghadapi masalah teknis saat menggunakan AI saya tahu cara menyelesaikannya sendiri.
Kualitas Informasi yang Dipersepsikan *(Perceived Information Quality - PIQ)*	Saya yakin dapat mencapai hasil belajar yang saya inginkan dengan menggunakan AI secara efektif.
	Informasi yang disediakan oleh AI akurat dan bebas dari kesalahan.