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Research Article

ADOPTION OF ARTIFICIAL INTELLIGENCE IN STEM LEARNING: EXAMINING THE EFFECTS OF PERFORMANCE, EFFORT, AND SOCIAL FACTORS

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Abstract
Artificial Intelligence (AI) has recently gained prominence in higher education, particularly in Science, Technology, Engineering, and Mathematics (STEM) disciplines, offering transformative potential for learning and innovation. However, students' adoption of AI tools is influenced by multiple psychological and contextual factors. This study aims to examine the effects of performance expectancy, effort expectancy, and social influence on students' behavioral intentions to integrate AI into STEM education. A quantitative research design was employed, involving 203 undergraduate students from the University of Jambi and Universitas PGRI Mahadewa Indonesia. Data were analyzed using Structural Equation Modeling (SEM) through SmartPLS 3.3 to identify direct and mediating relationships among variables. The findings revealed that performance expectancy significantly influenced students' behavioral intentions, indicating that perceived usefulness of AI outweighs ease of use in determining adoption. Effort expectancy also had a substantial effect and mediated the relationship between performance expectancy and behavioral intentions, while social influence showed no significant impact. These results highlight that students' engagement with AI in STEM learning is driven more by perceived academic and functional benefits than by peer or social reinforcement. The novelty of this study lies in its integration of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework with the STEM education context in developing countries, providing new empirical insights into AI adoption behavior. The study recommends designing AI-supported learning environments that emphasize practical benefits, user-friendly interfaces, and pedagogical integration to enhance students' learning outcomes and technological readiness.

Keywords: Artificial Intelligence, Behavioral Intention, Effort Expectancy, Performance Expectancy, Social Influence, STEM

INTRODUCTION

Artificial intelligence (AI) has introduced transformative tools and methods to education and other industries. This situation demands understanding students'AI adoption considerations. Performance expectations and the perceived benefits of using technology for educational and non-educational aims affect adoption rates (Faqih & Jaradat, 2021). Students' AI views are also affected by effort anticipation (Andrews et al., 2021; Shal et al., 2024). In collaborative learning, peers and instructors matter (Habibi et al., 2023). Research shows that behavioral intention is a key determinant of technology use. UTAUT and TAM models are used to study AI adoption in many scenarios (Chatterjee et al., 2023). Higher education institutions have used ChatGPT and other AI tools for information accuracy, convenience of use, and perceived benefits (Menon & Shilpa, 2023).

This gap is critical because STEM education emphasizes problem-solving, analytical reasoning, and innovation—areas where AI has the potential to enhance engagement, critical thinking, and self-directed learning (Nuangchalerm, 2023; Tarumasely et al., 2024). In STEM applications, artificial intelligence is evaluated based on various variables, including the user's intention. Discovered that students' technology adoption is influenced by their university's prestige and intention to pursue a job (Aluri & Tucker, 2015). Meanwhile,emphasized the importance of trust in AI technology in determining usage intention, especially in nations with robust cultural backgrounds (Alshammari & Alshammari, 2024; Xu & Thien, 2025).

Recent studies emphasize AI's benefits in improving academic performance and flexibility in learning (Jain et al., 2022; Du et al., 2023), but they often overlook the interaction between psychological factors (expectancy beliefs) and social contexts that determine actual student adoption. This phenomenon also occurs in STEM education, where the utilization of artificial intelligence is recommended under appropriate guidelines and the instructor's involvement (Nam & Bai, 2023). Social and technological accessibility strongly influences educational technology adoption (Fetaji, 2023). The paper examines these elements to promote AI in education while addressing usability and societal issues. According to (Tian et al., 2024) students' digital usage affects the adoption of AI in classrooms, correlating AI technology performance with self-efficacy. The documents illustrate the application of AI in education for both scholarly and personal advancement. AI enables the enhancement of education effectively, even in STEM disciplines.

Behavioral objectives influenced by perceived usefulnes and perceive ease of use dictate the acceptability of instructional technology (Sun & Guo, 2022). Comprehending the rationale behind students' use of artificial intelligence is crucial as higher education increasingly engages with it. According to Andrews et al., (2021) UTAUT2 elucidates performance expectancy, effort expectancy, and social influence. This method enables researchers to identify behavioral and contextual influences on AI acceptance and to address usability and social challenges for the integration of AI in STEM education.

Universitas Jambi and Universitas PGRI Mahadewa Indonesia could examine students' adoption of AI in STEM education by investigating performance expectations, effort expectations, and societal impact. Understanding the factors that render artificial intelligence acceptable can assist universities in enhancing their AI inclusion programs inside STEM education. This research investigates student responses to artificial intelligence, usability, and social dynamics. This would enhance the digital reputation and educational standards of UNJA and University PGRI Mahadewa Indonesia.

LITERATUR REVIEW

Performance Expectations

This factor is vital to AI user acceptability. Click or tap here to enter text. Adopting AI technology in the banking industry is mostly driven by the perceived advantages of AI in increasing efficiency (Rahman et al., 2023; Agarwal et al., 2024). Students' academic performance and confidence were enhanced when the UTAUT paradigm was used for AI-based chatbots (Kennedy, 2023; Bouteraa et al., 2024). Younger generations are more inclined to reengage with AI-based technologies when they perceive tangible benefits from it (Bowman & Howie Huang, 2021; Barbul & Bojescu, 2023). Users' performance expectations are significantly linked to their first trust in AI-based chatbots (Adam et al., 2021; Stoilova, 2021). AI-driven digitalization in the MSME accounting sector enhances efficiency and user trust in technology (Bouwman et al., 2018; Ritter & Pedersen, 2020). The development of AI-based virtual assistants meets consumer performance expectations, particularly by accelerating task completion (García de Blanes Sebastián et al., 2022; Wald et al., 2023). Significance of performance expectations in education by highlighting how AI technology changes educational paradigms and increases students' motivation and independence in learning.

Using AI globally affects performance expectations in various industries and improves quality of life. Blockchain and AI in accounting courses to improve learning effectiveness and offer users substantial advantages (Glory Ugochi Ebirim et al., 2024). Several factors, including users' expectations of the benefits, affect the adoption of AI in the retail industry (Cubric, 2020; Fu et al., 2023). Adopting information technology, particularly AI, in government sectors is positively impacted by the expectation of its benefits. AI in Islamic banking services to increase client trust by delivering reliable and creative results. These results highlight the importance of performance expectations in determining the adoption and effective use of AI technologies in various fields.

H1: Performance Expectancy (PE) positively influences Behavioral Intention (BI).

H2: Performance Expectancy (PE) positively influences Effort Expectancy (EE).

Effort Expectancy

Effort expectations show how much consumers think a certain technology is simple to use, greatly impacting its adoption. Ease of use has significantly impacted users' willingness to engage with AI in their work, including in the field of education (Chocarro et al., 2023). Similarly, generation Z is more inclined to reuse AI-based solutions, such as mobile payments, when they see them as user-friendly (Barbul & Bojescu, 2023). Computerized accounting information systems, such as K-Soft, achieve more success in commercial environments when users perceive the system as straightforward and easily learnable, necessitating minimal training (Giabbanelli & Tawfik, 2020). This perceived ease of use can even be extended to the tourism sector (Cubric, 2020; Filieri et al., 2021; Samala et al., 2022). Furthermore, customer willingness to adopt AI has increased significantly due to its ease of use in UAE security systems (Zeroual & Zerouali Ouariti, 2022; Al Humaid Alneyadi & Normalini, 2023) (Humaid; Zero). Ease of use of AI is often perceived as a positive element that improves quality of life and is crucial for various applications. Furthermore, students' perceptions of the ease of use of AI-based chatbots are closely related to their self-confidence and academic performance, highlighting the importance of effort intention in supporting technology-based learning (Gokcearslan, 2020; Parsakia, 2023; Esiyok et al., 2025). These varying factors collectively emphasize that intention to invest effort is crucial in advancing the acceptance and application of AI technologies across many domains. Emphasizing user-friendly designs and reducing perceived effort in adopting AI frameworks can result in a wider array of options and enhanced satisfaction, hence optimizing the advantages of these technologies.

H3: Social Influence (SI) positively influences Behavioral Intention (BI).

H4: Social Influence (SI) positively influences Effort Expectancy (EE).

Social Influence

Social impact may be a fundamental factor influencing an individual's intention to utilize artificial intelligence (AI)-based innovation, as emphasized in the Unified Theory of Acceptance and Use of Technology (UTAUT). Generation Z, known as "digital native", is significantly influenced by their social environment in choosing to receive AI within the working environment, especially due to tall intentions from colleagues and administrators In addition, positive public attitudes towards AI significantly influence individuals to use this technology in daily activities (Cui & Wu, 2021). Encouragement from friends and teachers can also motivate the use of AI (Bhowmik et al., 2022; Chiu et al., 2023). Social influence factors can increase consumer purchase intention through social media marketing utilizing AI (Ali et al., 2020; Sidlauskiene et al., 2023; Salah & Ayyash, 2024). Furthermore, the decision to use or purchase a product is apparently greater when AI is involved in marketing (Dung Le et al., 2022; Huang & Rust, 2022). Another finding, shows how social influences, such as support from study groups and instructors, increase student enthusiasm. The introduction of AI technology into the classroom has changed the role of the teacher into one that is more collaborative, and teachers are encouraged to use the technology with strong social support.

H5: Effort Expectancy (EE) positively influences Behavioral Intention (BI).

H6: Performance Expectancy (PE) mediates the relationship between Effort Expectancy (EE) and Behavioral Intention (BI).

H7: Social Influence (SI) mediates the relationship between Effort Expectancy (EE) and Behavioral Intention (BI).

Intention to Use AI in STEM Education

The intention of using AI in STEM indicates a shift in the pedagogical paradigm towards a new approach, which uses data-driven, adaptive, and transformative sources. AI does not only act as a tool, but also to facilitate the development of digital literacy, including 21st century skills (Ng et al., 2023). The use of AI in STEM aims to form students who think reflectively, analytically, and creatively in solving problems, so that they are not just users of technology (Jang et al., 2022; Li et al., 2023). Empirical studies show that the implementation of AI in the context of higher education can improve the quality of learning, but it is necessary to pay attention to aspects of personalization, tutoring, and inclusive collaboration (Nixon et al., 2024). In the context of STEM education, the use of AI supports the achievement of deeper STEM competencies. However, this intention also raises ethical challenges that cannot be ignored. The use of generative AI such as ChatGPT in academic settings, for example, has the potential to create ambiguity and integrity challenges in academic work (Nam & Bai, 2023). In addition, the gap in access and digital literacy is also an important issue that can widen educational inequality. Therefore, the implementation of AI in STEM education must be accompanied by a policy framework that refers to ethical responsibility (Nuangchalerm, 2023). It is essential to ensure that digital transformation, within the framework of AI utilization in STEM education, is not solely technological but also humanistic, inclusive, and sustainable.

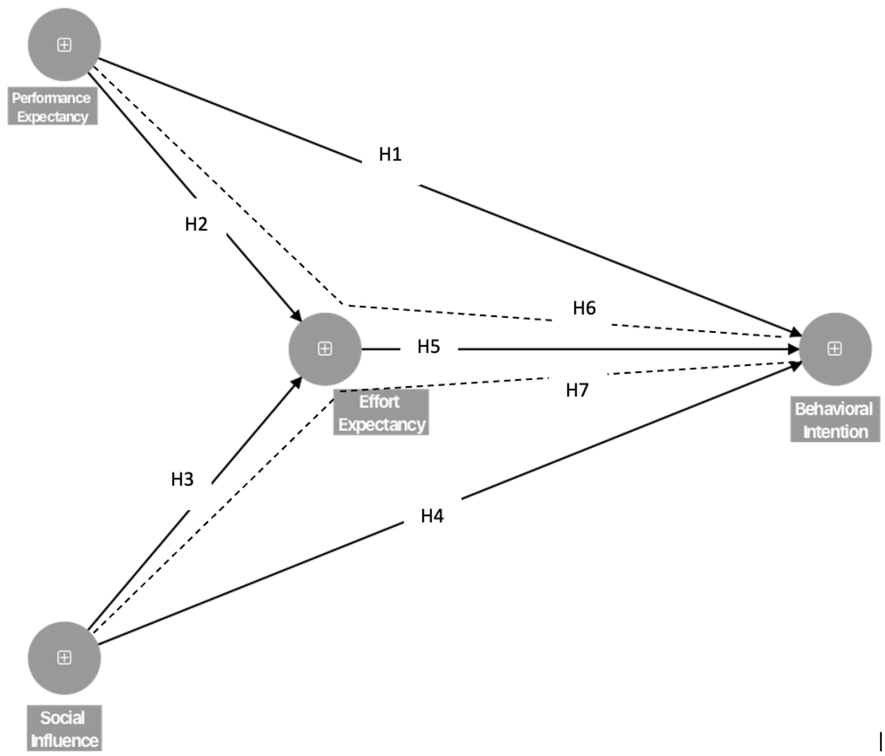

Figure 1. Proposed Model

RESEARCH METHOD

The research is a quantitative type using a survey approach that examines how performance expectations, social influence, and effort expectations impact the influence of the adoption of AI technology by students in STEM education. This research was performed at Universitas Jambi and Universitas PGRI Mahadewa Indonesia (UPMI), encompassing a population of 33,214 individuals. The sampling technique used in this study was convenience sampling. The G Power application was utilized to ascertain an adequate sample size, with G Power recommending 203 participants, all undergraduate students. A Google Forms survey was employed to gather data utilizing Cronbach's alpha and Pearson's product-moment correlation. Group disparities were analyzed utilizing the t-test. Data analysis was conducted via SEM-PLS facilitated by SmartPLS 3.3.

The estimate model's validity and reliability were tested, and other models validated the exogenous-endogenous coordinate relationship. This study aims to completely understand each variable's impact. There are two components of the questionnaire used in this study. The first part asks respondents about their demographics, and the second part has 40 items evenly spread across four research constructs: performance expectations (10 items, adapted from (An et al., 2023), effort expectations (10 items, adapted from (Venkatesh et al., 2003), social influence (10 items, 4 items) adapted from (Liang et al., 2023), 4 items adapted from (Pokrivcakova, 2019), and 2 items adapted from (Bardakcı & Alkan, 2019), and behavior intention (10 items, 5 items adapted from (Chai et al., 2021), and 5 items adapted from (Zhou et al., 2017). A 5-point Likert scale, with 1 denoting “strongly disagree” and 5 denoting “strongly agree”, is used for all assertions. Before being given to respondents, the questionnaire instrument underwent pre-testing to guarantee its validity and reliability. The respondents thought all of the questionnaires were clear and well-received.

The data collection instrument used in this study was a questionnaire. The 5-point Likert scale survey was filled by 203 legitimate respondents. The methodology included research design, sample size, sampling process, data collection method, validity and reliability test, variable measurement, and data analysis. Considering earlier research, the literature on AI was considered when creating the questionnaire (Chiu et al., 2023). The survey’s initial page provides information about the study’s goal and survey participants’ identities for convenience. The questionnaire's primary tool is a 5-point Likert scale, with 1 denoting “strongly disagree”, 5 denoting “strongly agree” or “strongly disagree”, and 5 denoting “strongly agree”. There are four primary sections of the questionnaire. Aspects of expected performance (AI) are covered in the first section, expected performance in the second, social influences on students are covered in the third, and aspects of expected performance (AI) regarding. Before the survey was conducted, four participants were chosen for pilot research to assess the questions’ clarity, improve the questions, and gauge respondents' comprehension. Some questions were removed or altered, and all feedback was meant to improve the survey. Two hundred eleven students received the questionnaires where only 203 of them returned the survey. 96.21% response rate makes it suitable for further examination.

This study meticulously evaluated data to address the research challenge and achieve its goals. Microsoft Excel was used to clean and code 203 valid respondents’ data for completeness and uniformity. Data missing or incomplete was removed from research. Descriptive statistics were used to summarize respondents' gender, age, and university affiliation using frequencies and percentages. Cronbach’s alpha was used to test questionnaire item internal consistency, with 0.7 or higher being satisfactory. To ensure relevance, simplicity, and validity, 10 professional professors and students scored the statements using CVI (Liu et al., 2021; Soriano, 2021). SmartPLS 3.3 examined construct correlations using SEM-PLS (Shmueli et al., 2019). Assessed the measuring model’s validity (AVE convergent, Fornell-Larcker criterion, and HTMT ratio discriminant) and reliability (Cronbach’s alpha, composite reliability) (Afthanorhan et al., 2021).The structural model was evaluated using path coefficients (β), t-values, and p-values to test hypotheses and determine relationship significance. Model explanatory power was examined by computing R2, f2, and Q2. Finally, the data was reviewed in light of the study objectives to see how these research variables will effect STEM students’ AI technology acceptance.

RESULTS AND DISCUSSION

This study successfully collected data from 203 valid responses from undergraduate students at the University of Jambi and PGRI Mahadewa Indonesia University. The majority of respondents were female (69.5%) with an age range of 20–24 years. Descriptive statistics confirmed the assumption of a normal distribution for the main constructs. More detailed demographic data are presented in Table 1.

Table1. Participants’ profile N (203)

Demographics	Category	Frequency	%
Gender	Man	62	30.5%
	Women	141	69.5%
	Total	203	100%
University	Universitas PGRI Mahadewa Indonesia	146	71.9%
	Universitas Jambi	57	28.1%
	Total	203	100%
Age	< 20	41	20.2%
	> 20	162	79.8%
	Total	203	100%

Preliminary data analysis

The potential for common method bias (CMB) and multicollinearity was examined before data analysis. We employed the "variance inflation factor, or VIF," to evaluate multicollinearity. Every VIF value must be less than three (Sarstedt et al., 2020)Click or tap here to enter text.. Since the calculated VIF ranged from 1.030 to 2.709, multicollinearity was not indicated (Table 2). The presence of CMB was then tested using Harman's single factor. According to his research, loading every measurement item in the data set at once produced a total variance of 44.678%, below the 50% cutoff point, suggesting the absence of CMB (Podsakoff et al., 2003). According to this analysis, the data is appropriate for additional analysis since it passes the CMB test (total variance is less than 50%) and the multicollinearity test (all VIF values are less than 3).

Table 2. Multicollinearity

Construction	BI	EE
EE	2,641	-
PE	2,709	1,030
SI	1,043	1,030

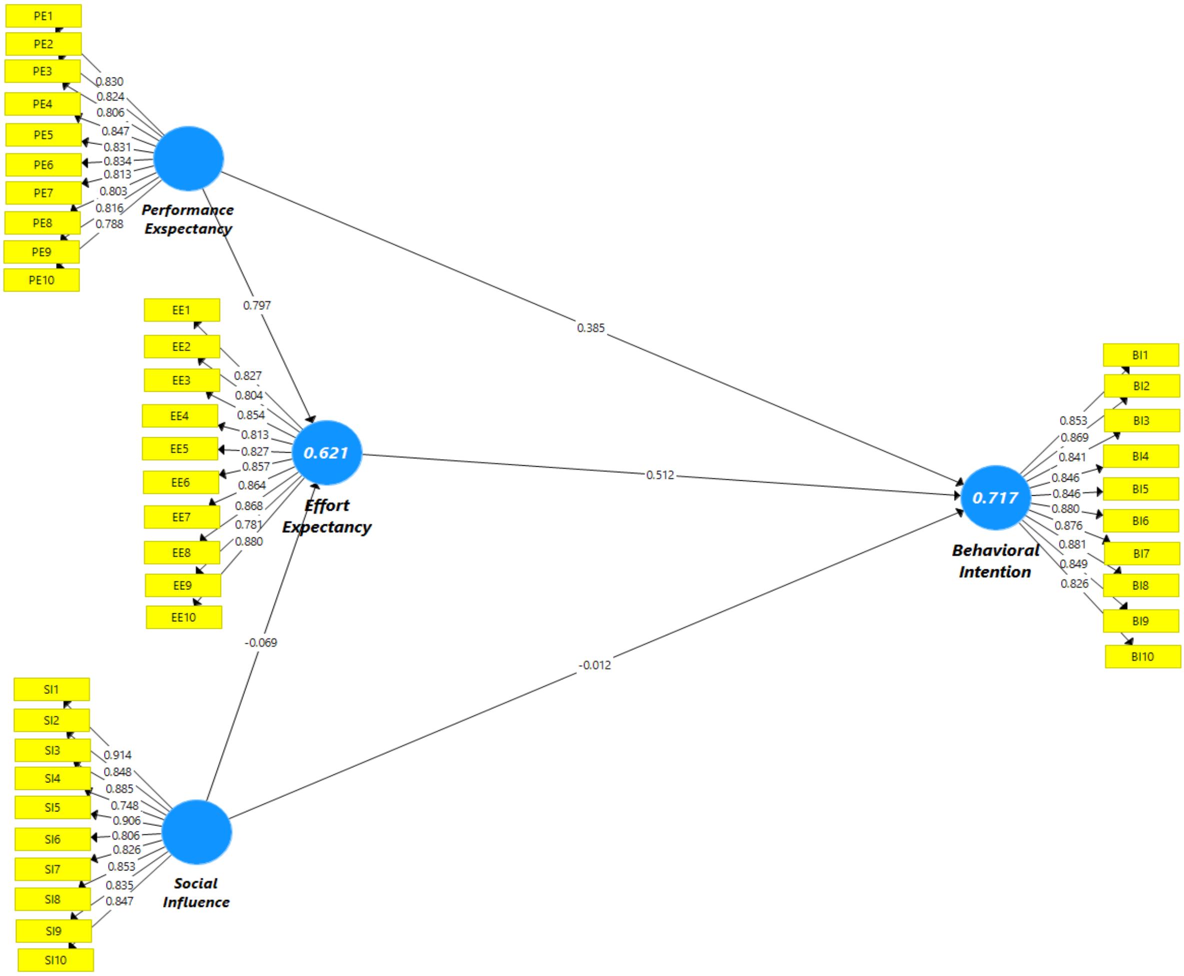

Figure 2. Structural Model Evaluation

Measurement model

The validity and reliability of the scales (constructs) and measurement items (indicators) were examined before testing the suggested hypothesis (Sarstedt et al., 2021). First, each indicator's loading was assessed. Acceptable item loading is indicated by a loading ≥0.708. According to Table 3, each element's loading falls between 0.788 and 0.916 for PE, 0.804 and 0.880 for EE, 0.748 and 0.953 for SI, and 0.824 and 0.890 for BI. Every value is higher than what is advised, suggesting that every aspect has enough item reliability. Second, internal consistency was assessed using composite reliability (CR) and

Cronbach's Alpha (α). It is advised that CR and α have minimum acceptable values of 0.7 and not ≥0.95. Every design satisfied this requirement (Table 3). Third, evaluation of the signs of convergence by examining the "Summary Mean Variance – AVE". The minimal AVE value is used to lower the value of 0.5. Table 3 shows that each construct converges because its AVE values (PE = 0.671, EE = 0.703, SI = 0.718, and BI = 0.734) are significantly higher than 0.5. Verifying the cross-loading verifies the convergence's accuracy and demonstrates that the item is loaded substantially by the intended configuration.

Table 3. Internal and convergent validity assessment

Construction	Item	Loading	α	Rho_A	CR	AVE
Performance Expectancy (PE)	PE1	0.830	0.946	0.946	0.953	0.671
	PE2	0.824				
	PE3	0.806				
	PE4	0.847				
	PE5	0.831				
	PE6	0.834				
	PE7	0.813				
	PE8	0.803				
	PE9	0.816				
	PE10	0.788				
Effort Expectancy (EE)	EE1	0.827	0.953	0.954	0.959	0.703
	EE2	0.804				
	EE3	0.54				
	EE4	0.813				
	EE5	0.827				
	EE6	0.857				
	EE7	0.864				
	EE8	0.868				
	EE9	0.781				
	EE10	0.880				
Social Influence (SI)	SI1	0.914	0.959	1,012	0.962	0.719
	SI2	0.848				
	SI3	0.885				
	SI4	0.748				
	SI5	0.906				
	SI6	0.806				
	SI7	0.826				
	SI8	0.853				
	SI9	0.835				
	SI10	0.847				
Behavioral Intention (BI)	BI1	0.853	0.960	0.960	0.965	0.734
	BI2	0.869				
	BI3	0.841				
	BI4	0.846				
	BI5	0.846				
	BI6	0.880				
	BI7	0.876				
	BI8	0.881				
	BI9	0.849				
	BI10	0.826				

Table 3 presents a research document analyzing the acceptance of AI in learning through a structural equation model, focusing on discriminant validity using the HTMT. The results display correlations among constructs— BI, EE, PE, and SI—with diagonal values (e.g., 0.857 for BI, 0.838 for EE) exceeding off-diagonal correlations (e.g., 0.813 between BI and EE, 0.785 between BI and PE), confirming distinct constructs as required for discriminant validity. This suggests that students' intentions to use AI in STEM education, their perceived of its ease and performance expectancy, and social influences are separate but interrelated factors. The HTMT analysis supports a reliable model for studying how AI enhances learning outcomes, addressing user acceptance through frameworks like UTAUT. The findings highlight AI's potential to transform education, provided it is user-friendly and perceived as beneficial, while social factors also play a key role in its adoption.

Table 4. Discriminant validity, HTMT

	BI	EE	PE	SI
BI	0.857	-	-	-
EE	0.813	0.838	-	-
PE	0.785	0.785	0.819	-
SI	0.089	0.069	0.172	0.848

Structural model

To evaluate the study's hypotheses, we bootstrapped the data (5000 sub-samples) (Hair et al., 2020). A structural equation model was used to study STEM education AI acceptance. Table 5 shows the results. The current study examines behavioral intention (BI), effort expectancy (EE), performance expectancy (PE), and social influence (SI). This study also analyzes how these constructs affect STEM education's use of AI technologies. This study examines five hypotheses, each with a path in the model, β (path coefficient), t-value, p-value, and assumption findings to determine statistical significance.

Hypothesis 1 (H1) reveals a substantial correlation between Effort Expectancy and Behavioral Intention (β = 0.521, t-value = 4.732, p-value = 0.000). This shows that students' intention to use AI tools like adaptive learning systems or AI tutors is greatly influenced by their perceived ease of use. Hypothesis 2 (H2) indicates a substantial correlation between behavioral intention and performance expectation (β = 0.385, t-value = 3.318, p-value = 0.001). Students' intention to utilize AI may be influenced by their idea that it will improve learning outcomes (e.g., grades or understanding). Hypothesis 3 (H3) indicates a strong correlation between Performance and Effort Expectations (β = 0.797, t-value = 17.272, p-value = 0.000). This shows that performance gains affect perceived ease of use, supporting AI's appeal in education. Conclusions from Hypotheses 4 and 5 are insignificant: Social Influence does not significantly predict Behavioral Intention (β = 0.012, t-value = 0.123, p-value = 0.808) or Effort Expectancy (β = 0.066, t-value = 1.236, p-value = 0.217), suggesting that peer or societal pressures do not significantly impact students' STEM education AI adoption decisions.

Table 5. Hypothesis testing

H	Path	β	t-value	p-values	Assumption
H1	EE → BI	0.521	4,732	0.000	Yes
H2	PE → BI	0.385	3.318	0.001	Yes
H3	PE → EE	0.797	17,272	0.000	Yes
H4	SI → BI	- 0.012	0.243	0.808	No
H5	SI → EE	- 0.069	1.236	0.217	No

Indirect effect assessment

Effort Expectancy (EE) mediated Performance Expectancy (PE) and Behavioral Intention. This shows that students' perceptions of AI's benefits indirectly influence their plans to use AI in STEM education for higher education. Social impacts on predicted effort did not significantly affect behavioral intention. This implies that social influences do not deceive behavior through expected effort, even when they directly affect students' AI readiness. The study found that execution expectation mediates the relationship between behavioral intent and execution expectation, but not anticipation or social impact.

Table 6. Indirect effects

Hypothesis	β	Mean	STDEV	T Statistics	P values
H6: PE → EE → BI	0.408	0.405	0.097	4.218	0.000
H7: SE → EE → BI	-0.035	-0.035	0.026	1.326	0.185

This research examines instructors' and students' behavioral intents to integrate AI into STEM education. Performance expectancy (PE) significantly affects behavioral intention (BI). Students want to use AI in STEM learning because they think it improves comprehension, task completion, and learning efficiency. In pursuit of academic excellence, they value intelligent tutoring systems and adaptable learning platforms (Venkatesh, 2022). These findings support the UTAUT, which states that performance expectancy drives technology adoption, especially when people believe technology can improve their performance (Venkatesh, 2022). The substantial correlation between effort expectancy (EE) and performance expectancy ($\beta = 0.797$, $p < 0.001$) indicates that students regard AI as easy to use when they grasp its practical benefits, reducing perceived adoption barriers.

This supports recent findings that students are more likely to use AI if they find it useful and simple. AI-powered learning aids that simplify exercises or provide immediate feedback reduce cognitive burden and improve use. AI in STEM education will promote inclusive cooperation and customised learning (Zafari et al., 2022; Nixon et al., 2024). These technologies demonstrate how AI can improve student engagement and achievement (He et al., 2021; Krempkow & Petri, 2022). These findings show that performance and effort expectations affect students' AI acceptance and that instructional technology should prioritize usability and perceived worth. To make STEM learning and academic performance easier, this argument stresses merging AI technology with student needs.

Effort Expectancy (EE) influences STEM students' AI technology use. The high correlation between EE and BI shows that students are more inclined to use AI-based solutions like intelligent tutoring systems and adaptive learning programs in their coursework when digital platforms are intuitive and easy to use. This supports prior studies demonstrating learners choose easy-to-use devices (Dash et al., 2023). EE also mediates Performance Expectancy and Behavioral Intention, showing that students are more likely to use AI systems that are easy to use and help them learn information. Thus, AI applications that simplify STEM learning, improve comprehension, and encourage reflective thinking and problem-solving can boost adoption (Vasconcelos & dos Santos, 2023). These findings can help schools prioritize the design and implementation of successful, accessible, and student-centered AI systems.

Social Influence (SI) did not affect Behavioral Intention or Effort Expectancy, indicating that peers, educators, and social networks do not strongly support AI in STEM education. Institutional and peer support alone may not be enough to promote AI-based tutoring and adaptive learning platforms. AI systems may not learn social norms with educational or institutional support (Yusop et al., 2021; Habibi et al., 2023). These findings contrast technology adoption research that stresses social impacts in collectivist settings or tightly connected educational communities. Individual AI value (Performance Expectancy) and ease of use come before societal reasons in adoption decisions. Personal experiences and perceived practical benefits are more important than social factors in students' adoption of AI technologies like ChatGPT (Korzynski et al., 2023; Vasconcelos & dos Santos, 2023; Duong et al., 2024). To make SI more relevant, universities can promote STEM AI utilization through peer-to-peer or collaborative learning projects. Due to parental, mentor, and peer influences on STEM performance (Luo et al., 2022). Institutions can improve education by integrating AI and social learning with individual and societal viewpoints. This sophisticated perspective emphasizes the need for specialized academic technology adoption methods that balance individual and social characteristics to deploy AI in education.

CONCLUSION

This study concludes that performance expectancy and effort expectancy are the dominant factors influencing STEM students' intentions to adopt artificial intelligence (AI) in their learning processes, while social influence plays a comparatively minor role. The mediating effect of effort expectancy highlights the critical importance of designing AI systems that are user-friendly, pedagogically relevant, and seamlessly integrated into academic contexts. This suggests that students are more likely to engage with AI tools when they perceive them as both beneficial to their academic performance and easy to use without excessive cognitive or technical barriers. The implications of these findings emphasize that higher education institutions should not only adopt AI technologies but also focus on ensuring that their implementation aligns with students' learning needs and digital readiness. Universities must invest in developing intuitive, accessible, and educationally purposeful AI platforms that can support personalized learning, adaptive feedback, and data-driven instruction. Additionally, faculty and curriculum developers should receive professional training to integrate AI tools effectively, fostering an environment where technology enhances rather than complicates the learning experience. Theoretically, this research extends the applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) model within the context of higher education by confirming the mediating role of effort expectancy in shaping students' behavioral intentions. Practically, it underscores the importance of usability and perceived value in driving technology adoption among students. By prioritizing human-centered AI design and pedagogical alignment, educational institutions can enhance learning efficacy, efficiency, and accessibility ultimately fostering a more adaptive, innovative, and technology-literate generation of STEM learners.

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AUTHOR CONTRIBUTIONS

I Wayan Sumandya was responsible for conceptualization, validation, investigation, and project administration. I Wayan Widana contributed to conceptualization, validation, supervision, resources, funding acquisition, and writing – review & editing. Robi Hendra handled methodology, software, validation, formal analysis, and writing – original draft preparation. Rahma Ayu Safitri was in charge of investigation, data curation, and visualization.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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