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ARTIFICIAL INTELLIGENCE IN EDUCATION: EVIDENCE FROM MALAYSIAN ACCOUNTING STUDENTS

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Abstract
Artificial Intelligence (AI) has significantly permeated in every sphere of human life, specifically education. To date, although developed nations have extensively embedded it in teaching and learning, emerging economies are still in the infancy stages, widening the gaps in educational digital performance. Intrigued to bridge these gaps, the researchers aim to investigate what factors would influence students to adopt AI in education within the Malaysian context. Following the Unified Theory of Acceptance and Use of Technology (UTAUT), the researchers predict that performance expectancy, effort expectancy, social influence, and facilitating conditions would significantly impact students' adoption of AI. Additionally, they predicted that a growth mindset would also play a significant role. Based on 200 data sets, the multiple regressions of PLS-SEM 3 confirmed that all predicted variables are significantly related to students' adoption of AI. The results contribute competent insights to policymakers, higher educational institutions, and academicians in formulating interventions for accelerating the adoption of AI among higher educational institutions. Hence, embracing AI is aligned with the aspiration of the United Nations' sustainable development goals for ensuring inclusive, equitable, and quality education for all by 2030.
Keywords: Artificial Intelligence, Education, Accounting, Students

INTRODUCTION

Artificial Intelligence (AI) has tremendously altered every sphere of modern life, including education. The notable change is the rapid transformation of classrooms into more dynamic and technology-driven environments. AI offers unprecedented opportunities to personalize learning, automate administrative tasks, and support students and teachers in meaningful ways. From intelligent tutoring systems to real-time data analytics, AI enhances knowledge delivery, besides redefining what it means to teach and learn in the 21st century.
Although educational research has been interested in AI for 30 years, its potential in pedagogy has been seriously explored recently (Wu et al., 2026). AIs are not new to developed countries, however, for a country in emerging economies, like Malaysia, these machine learning techniques are still in the infancy stage. Damerji and Salimi (2021) articulated that Artificial Intelligence (AI) is one of the prominent innovations in education and is expected to revolutionize the future educational system embedded with advanced technologies, including data mining, natural language processing, neural networks, and algorithms.
To date, many have invented AI application tools to cater to the needs of educators, administrators, and students. Amongst the popular tools are ChatGPT, Deepseek, Grammarly, Quiltbot, Turnitin, Perplexity.ai, Gemini, Elicit, and Microsoft Copilot (Malik & Amjad, 2025; Maltseva & Pavlova; 2025; Noor, 2025). Students and teachers have indeed gained tremendous benefits from AI tools. First is personalized learning whereby students would learn according to their learning styles and paces. Those tools give feedback and offer specific guidance individually, thus improving their learning outcomes. Students can explore subjects aligned with their interests through gamification, simulations, and chat-based tools. The students are aware that AI tools can enhance their educational performance. Besides, their expectation was that these tools would reduce their effort.
Interestingly, AI accommodates disability students or those with learning challenges by adjusting materials to suit their abilities. Educators also can automate grading the students' quizzes, multiple-choice questions and even essays. AI allows one teacher (or system) to reach many learners. Apart from that, AI can detect at-risk students through performance patterns. Educators can use predictive analytics for curriculum improvement and understand how students engage with content in real time. Additionally, AI tutors or chatbots provide learning support outside classroom hours.However, AI also has drawbacks (Govindarajoo et al., 2025; Jie & Kamrozzaman, 2024). For

instance, it reduces meaningful and physical interaction between students and teachers, weakening social and emotional learning. Moreover, students tend to rely more on chatbots or automated feedback, missing opportunities for personalized guidance from educators. AI tools often require stable internet, modern devices, and digital literacy. Unfortunately, those in remote or low-income areas who do not have access to the network would be left behind, thus, widening the digital divide between the groups.
Indeed, many are sceptical, and doubtful of the AI capability (Funa & Gabay, 2025; Khan et al., 2025; Mohammed et al., 2024). Some complain that they must put extra effort and time to learn and adopt the AI tools. Even worse, closed people reluctant to help and support them. Those people perceived that students may become too reliant on AI for answers and thus reducing critical thinking and problem-solving skills. Additionally, these people taught that students misuse AI to generate essay and solve problems for them without they understand the content. Specifically, students with fixed mindset, they reluctant to engage with AI as they are familiar with conventional system.
While AI in education presents notable challenges, such as reduced human interaction, lack of support from surrounded people, resistible to change, in confidence with the performance, poor infrastructure, data privacy concerns, resistible to change and potential bias, its benefits tend to outweigh these challenges when properly managed (Salloum et al., 2024). Thus, with responsible design and integration, the advantages of AI in education can significantly surpass its limitations, contributing to a more inclusive, efficient, and adaptive learning environment.
Despite setbacks, learners can reap bountiful pedagogical opportunities. The expectation is that AI can leverage the best attributes of technology and humans for the best outcome of students. Although AI have been greatly emphasized in developed countries, these learning machines are scarcely adopted by countries in emerging economy including Malaysia (Saravanan & Kamrozzaman, 2025). Indeed, the demand for AIs ignites the interest of educational disciplines. As such what are the best model of AI for Malaysian students need to be explored. Emulating UTAUT model (Venkatesh et al., 2003) and Growth Mindset Theory (Dweck, 2006), the study aims to investigate the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, and growth mindset on student's artificial intelligence adoption in Malaysian context.
The following of the paper will proceed by reviewing literature, followed by highlighting the adopted research methodology. Next, it presents the results and offers conclusions, theoretical and practical implications and limitations, besides recommendations for future research.

LITERATURE REVIEW

Artificial Intelligence Adoption in Education

As AI continues to grow rapidly in educational environments worldwide, Malaysia is still at the infancy phases of embracing this technology. Studies indicate that, despite the Ministry of Higher Education's efforts to promote digitalization through programs such as the Malaysia Education Blueprint (2015 - 2025), the adoption of AI tools in classrooms is inconsistent across the nation (Ahmad & Rathakrishnan, 2025). Some educators and students are still leaning on traditional methods, hampered by issues like inadequate infrastructure, skills gap, ethical dilemmas, and uncertainty about the reliability of AI (Boison, 2025). These challenges contribute to slower pace of AI adoption compared to more digitally mature education systems.
However, despite these structural and readiness challenges, student interest in AI has been on the rise in recent years. The widespread availability of AI tools like ChatGPT, Genie, Grammarly, and other smart learning assistants, has started to change students' expectations of digital learning environments. Studies show that Malaysian students, especially in higher education, are becoming more aware of AI's potential to enhance learning efficiency, provide tailored feedback, and support self-directed study habits (Hamidon et al., 2024; Noor, 2025). This growing openness suggests that while institutions may not be fully prepared, students' views and intentions towards AI adoption are evolving positively.
Given this contrasting landscape of gradual institutional adoption but increasing student interest, there is a pressing need to understand what factors influence students' readiness to engage with AI technologies. To address this need, the present study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) in conjunction with Growth Mindset Theory. These frameworks help us examine how performance expectancy, effort expectancy, social influence, facilitating conditions, and a growth mindset can serve as predictors of students' intentions to embrace AI in Malaysia.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003) offers a well-rounded framework for analyzing technology acceptance. This theory highlights four key factors that influence behavioral intention towards adoption of new technology, i.e; performance expectancy, effort expectancy, social influence, and facilitating conditions. This model has been widely used to explore how AI is adopted in educational contexts.
Research indicates that students are more likely to embrace AI tools when they recognize clear advantages in their learning performance, such as enhanced understanding or greater efficiency (Abulail et al., 2025; Acosta et al., 2024; Wu et al., 2022). In the perspective of effort expectancy, students tend to favor AI platforms that are straightforward and do not require too much effort (Abdelazim et al., 2025; Ke & Ke, 2025). Social influence is another factor, especially in institutes where educators, peers, or administrators advocate for AI usage (Jang, 2024;

Wu et al., 2022). Moreover, having suitable facilitating conditions in place such as access to technology, training, and technical assistance, may further encourage students to adopt these tools (Abdelazim et al., 2025; Abulail, et al., 2025; Boison, 2025). These findings highlight how well-suited the UTAUT model is for examining the intentions behind AI adoption in education.

Growth Mindset Theory

Growth mindset theory, introduced by Dweck (2006), draws a line between those who believe intelligence can grow (the growth mindset) and those who think it is fixed (the fixed mindset). People with a growth mindset are more inclined to tackle challenges, push through tough times, and view learning as an ongoing journey that can always be improved. This perspective significantly impacts their motivation, engagement, and willingness to explore new learning methods, especially in tech-driven environments.

In the context of AI adoption in educational settings, growth mindset plays a significant role in shaping how students interact with AI-driven learning tools. Growth mindset learners tend to be eager to experiment with AI platforms, and view AI as a valuable resource for boosting their learning abilities (Zhai & Li, 2025). Studies have shown that integrating growth mindset concepts into AI systems can enhance students' resilience and promote positive learning behaviors (Chow & To, 2025; Yu & Tao, 2025), helping them reinterpret mistakes as opportunities for growth, sustain motivation over time, and develop greater confidence in tackling unfamiliar or challenging tasks.

Research Framework and Hypotheses Development

Based on the UTAUT model and growth mindset theory, this study framework suggests that factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, and growth mindset significantly influence students' willingness to adopt AI in their educational journeys. The UTAUT constructs have proven to be reliable indicators in technology adoption research, and the growth mindset enriches this model by adding a psychological aspect that affects learning behaviors in AI-focused environments. Together, these viewpoints offer a comprehensive understanding into the adoption of AI. Based on the current study conceptual framework (Figure 1), the following hypotheses are formulated:

H1: Effort Expectancy (EE) significantly impacts Artificial Intelligence Adoption (AIA) among Malaysian students.

H2: Facilitating Conditions (FC) significantly impact Artificial Intelligence Adoption (AIA) among Malaysian students.

H3: Growth Mindset (GM) significantly impacts Artificial Intelligence Adoption (AIA) among Malaysian students.

H4: Performance Expectancy (PE) significantly impacts Artificial Intelligence Adoption (AIA) among Malaysian students.

H5: Social Influence (SI) significantly impacts Artificial Intelligence Adoption (AIA) among Malaysian students.

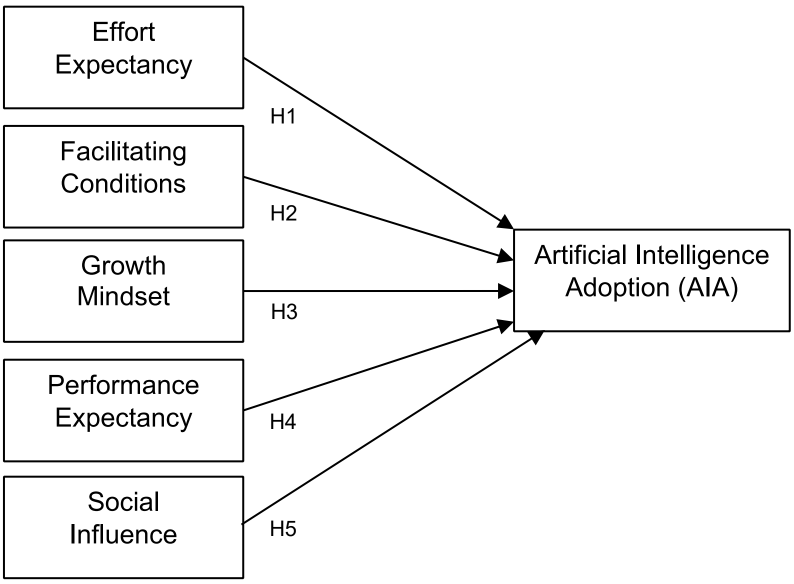

Figure 1. Conceptual framework

RESEARCH METHODOLOGY

Research Design

The study conducted a survey, utilising a quantitative approach, which included descriptive and positive analysis to examine research objectives and answer research questions. Adopting a cross-sectional technique, the researchers distributed a set of questionnaires to selected respondents at a point in time. The respondents were informed to answer without the researchers' interference.

Population and Sample

The population of this study is Malaysian students from Universiti Teknologi MARA of Kelantan campus. Approximately 500 sets of questionnaires were randomly emailed to the students, and 212 replied, representing a 42.4% response rate. After cleaning and filtering, the researchers rejected 12 of them due to missing items or inappropriate responses. Finally, a total of 200 data points remained for further analysis.

Measurement

The study adapted five independent variables, namely growth mindset, performance expectancy, effort expectancy, social influence, facilitating conditions, and one dependent variable, which is artificial intelligence adoption. Measurement items of those variables have been verified by past studies (Abdelazim et al., 2025; Abulail et al., 2025; Acosta et al., 2024; Boison, 2025; Chow & To, 2025; Jang, 2024; Ke & Ke, 2025; Wu et al., 2022). This study utilised a five-point Likert scale, ranging from strongly disagree to strongly agree (1 to 5).

Preliminary analysis

Initially, the researchers perform tests for normality. Findings revealed that all items were within normal distribution, indicating that all skewness and kurtosis values were between -1 and +1, within the threshold values, as suggested by Hair et al. (2021).

Demographic Profiles

The findings indicated that out of 200 respondents, 160 or 81% were females, while the remaining 38 or 19% were males. The majority of them were between 21 and 23 years (160 or 80%), followed by 24 to 26 years (25 or 12.5%), under 20 years (20 or 10%), and above 27 years (10 or 5%). In terms of programs, 110 respondents (55%) were pursuing a Diploma, 80 (40%) were in a Degree program, and the remaining 10 (5%) were in a Master's program. Finally, most students come from a family income bracket between RM5000 to RM7499 (85 or 42.5%), followed by RM7500 to RM10,000 (50 or 25%), more than RM10,001 (45 or 22.5%), and RM2501-4999 (20 or 10%).

Measurement Model

In analysing data, the researchers employed the Structural Equation Model (SEM) of Smart Partial Least Squares (PLS-SEM) version four (4). This analysis focused on prediction instead of testing the entire UTAUT and Mindset model. The analysis examined 2 models. The first model is a measurement model that evaluates the goodness of data to ensure all the data meet reliability and validity thresholds. In this model, the researchers examined whether the data fulfil convergent validity requirements based on items' loading, composite reliability, and average variance extracted. Results indicated that factor loading values for all items were from 0.717 to 0.902 above the threshold value of 0.5 (Hair et al., 2023). The composite reliability (CR) values were between 0.877 to 0.947, exceeding the value of 0.7, suggested by Hair et al. (2023). Additionally, all the Average Variance Extract (AVE) values were higher than 0.5, indicating that the data are fit (Hair et al., 2023). Hence, none of the items were deleted, and they continued for further analysis. Table 1 depicts the measurement model.

Table 1. Measurement Model

Measurements	Items	Loading	AVE	CR
Behavioural Intention (AI Adoption)				
I intend to adopt AI	AIA 1	0.813	0.718	0.947
I predict I will adopt AI in the future	AIA 2	0.894		
I have had to adopt AI in recent years	AIA 3	0.724		
I intend to learn more about AI	AIA 4	0.902		
I intend to consider adopting AI	AIA 5	0.890		
I intend to adopt it because it improves my knowledge in general	AIA 6	0.827		
I intend to adopt it for my career prospects	AIA 7	0.867		
Performance Expectancy				
I find AI is useful in my studies	PE 1	0.826	0.673	0.925
AI enables me to accomplish tasks more quickly	PE 2	0.838		
AI increases my productivity	PE 3	0.861		
AI increases my chances of getting good academic results	PE 4	0.805		
AI enables me to spend less time on routine tasks	PE 5	0.777		
AI improves the quality of my studies	PE 6	0.815		
Effort Expectancy				
My interaction with AI is clear and understandable	EE 1	0.740	0.588	0.877
I find AI easy to use	EE 2	0.796		
Learning to operate AI is easy for me	EE 3	0.701		
I have the necessary knowledge to adopt AI	EE 4	0.845		

I require less effort to operate AI	EE 5	0.746		
Social Influence				
My family members think that I should adopt AI	SI 1	0.766	0.616	0.906
My friends think that I should adopt AI	SI 2	0.792		
My faculty thinks that I should adopt AI	SI 3	0.820		
My university encourages me to adopt AI	SI 4	0.838		
People who are important to me have been supportive and have influenced me to adopt AI	SI 5	0.776		
Adopting AI elevates the student's reputation	SI 6	0.710		
Facilitating Conditions	FC1	0.704	0.630	0.911
I have the necessary resources to adopt AI	FC2	0.815		
I have the necessary knowledge to adopt AI	FC3	0.782		
I have support from a person or a group of persons to use AI	FC4	0.844		
Individual formal training on AI during my studies influenced my interest in IT usage for AI	FC5	0.761		
My university has the technology resources to adopt AI	FC6	0.848		
Growth Mindset	GM1	0.717	0.673	0.923
The opportunity to adopt AI is challenging	GM2	0.730		
When I fail to understand AI tools, I plan to try harder the next time I work on it	GM3	0.795		
I prefer to adopt AI tools that force me to learn new things.	GM4	0.763		
The opportunity to learn I tools is important to me	GM5	0.827		
I do my best when I and working with AI tools	GM6	0.781		
With AI tools, I try hard to improve on my past performance	GM7	0.724		
The opportunity to extent my abilities with AI tools is important to me.	GM8	0.717		
When I have difficulty solving a problem, I enjoy trying AI tools.	GM9	0.751		

Discriminant Validity

The study examined the convergent validity to ensure data are distinct from one another by performing the Heterotrait-Monotrait ratio of correlations (HTMT) criterion. Results indicated that all values were between 0.283 to 0.823, below the values of 0.85 (Kline, 2015), and 0.90 (Hanseler et al., 2015), showing that they were no issues of multi-colinearity. Table 2 indicates the HTMT criterion of the discriminant validity.

Table 2. Discriminant validity

	AIA	EE	FC	GM	PE	SI
AIA						
EE	0.440					
FC	0.749	0.283				
GM	0.785	0.317	0.798			
PE	0.795	0.395	0.723	0.745		
SI	0.782	0.366	0.794	0.784	0,823	

The researcher also examined the Variance Inflation Factor (VIF) values of all predictor constructs to test the collinearity in the structural model. The VIF is another measure of collinearity. The results revealed that all the VIF's values were below 5, indicating that the collinearity between is free from the inheritance (Hair et al., 2021).

Structural Model

The study examined data in a structural model. In this model, the analyses focused on testing hypotheses and determining whether the proposed relationships were acceptable or rejected. The results indicated that the R-squared (R^2) and adjusted R-squared (R^2adj) values were 0.692 and 0.685, respectively. In other words, all the independent variables, namely Effort Expectancy, Facilitating Conditions, Growth Mindset, Performance Expectancy, and Social Influence, explained 69.2% variance of the endogenous construct of Artificial Intelligence Adoption ($R^2 = 0.692$). The R^2 value from 0 to 1 represents the greatest level of predictive accuracy. Meanwhile, the R^2 values of 0.75, 0.50, and 0.25 are associated with strong, moderate, and weak, respectively (Hair et al., 2021). Hence, the value of 0.692 was deemed moderate.

The results showed that Effort Expectancy (β1; 0.130, t=3.257, ***p<0.001), Facilitating Conditions (β2; 0.151, t=2.074, **p < 0.05), Growth Mindset (β3; 0.246, t=3.149, ***p < 0.001), Performance Expectancy (β4; 0.264, t=2.899, ***p< 0.001), and Social Influence (β5; 0.216, t=2.068, **p < 0.05), indicating all relationships between variables were positively significant. Table 3 shows the results of hypothesis testing, while Figure 1 depicts the Structural Model.

Table 3. Hypotheses Testing

Hypothesis	**Estimate**	**S.E**	**T**	**p-value**	**Relationship**
H1: EE ----> AIA	0.130	0.040	3.257	0.001	Support
H2: FC ----> AIA	0.151	0.073	2.074	0.039	Support
H3: GM ----> AIA	0.246	0.078	3.149	0.002	Support
H4: PE ----> AIA	0.264	0.091	2.899	0.004	Support
H5: SI ----> AIA	0.216	0.105	2.068	0.039	Support

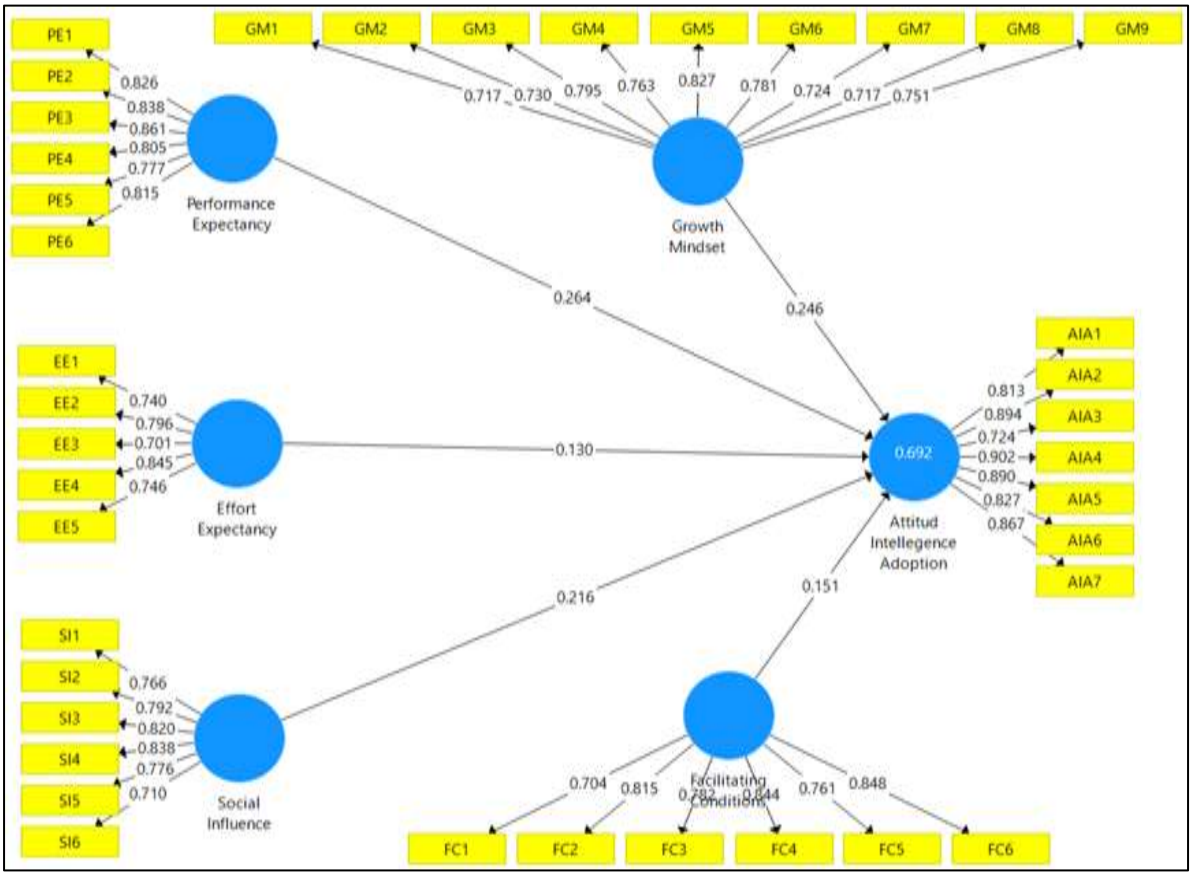

Figure 2. Structural Model

DISCUSSION

The first research objective is to examine the impact of effort expectancy (EE) on Artificial Intelligence Adoption (AIA) among Malaysian students. Results supported the notion that effort expectancy has a significant impact on Artificial Intelligence Adoption (β1; 0.130, t = 3.257, p < 0.001). The results aligned with the UTAUT model (Venkatesh et al., 2003) and literature (Abdelazim et al., 2025; Ke & Ke, 2025), such as in tax digitalization (Zakaria et al., 2024) and adoption of blockchain among auditors (Handoko & Lantu, 2021). Hence, the higher the students' expectation that AI adoption is effortless, the more likely they were to adopt, and thus HI is accepted. Thus, the majority of respondents are from Generation Z, who are digitally savvy and therefore adopting AI would be at their fingertips that does not require them to put a lot of effort.

Next, the second research objective is to examine the impact of facilitating conditions on Artificial Intelligence Adoption (AIA). Similarly, the results were supported (β2; 0.130, t = 2.074, p < 0.05). The higher the students perceived that the surrounding conditions would facilitate AIA, the more likely the students were to adopt it. Indeed, when the infrastructure supports technology, there is less likely problem of internet interruption and therefore the students would passionately ready to adopt AI.

The third objective examines the impact of the growth mindset on AIA. The results are in tandem with growth mindset theory (Dweck, 2006) and also supported (β3; 0.246, t = 3.149, p < 0.05) that the higher the students' growth mindset, the more likely they were to adopt AI; therefore, H2 and H3 are accepted. Indeed, students who are in millennium era believe that abilities, intelligence, and skills can be developed through dedication, and adopting AI can realize their inspiration.

Additionally, the fourth objective examines the impact of performance expectancy (PE) on Artificial Intelligence Adoption (β4; 0.264, t=2.899, p < 0.001). Results supported the UTAUT model (Venkantesh et al., 2003) and literature (Abulail et al., 2025; Acosta et al., 2024; Wu et al., 2022 ; Zakaria et al., 2024). Despite studies being carried out in different contexts, the findings revealed similar outcomes: the higher the expectation that artificial intelligence (AI) would lead to high performance, the more likely the students were to adopt AI. Many students who realised that AI would raise their educational performance would persistently adopt in pursuit of academic excellence. Hence, H4 is accepted and supported.

Finally, the fifth objective examines the impact of social influence on AIA. Likewise, the findings were supported (β5; 0.130, $t = 3.257$, $p < 0.001$) and were consistent with the UTAUT model and prior literature (Jang, 2024; Wu et al., 2022; Zakaria et al., 2024). The higher the students' expectations that their social groups will support them in adopting AI, the more likely they are to embrace it. H5 were also accepted. Hence, students are motivated to adopt AI, when they perceived that the surrounded social groups such as colleagues, educators, families and neighbours encourage them to adopt it.

CONCLUSION

The study has achieved its objectives and answered all research questions. Results indicated that all predictive factors, namely effort expectancy, facilitating conditions, growth mindset, performance expectancy, and social influence, have significant impacts on AIA and could explain students' intention to adopt AI. The Unified Theory of Acceptance and Use of Technology, integrated with the Growth Mindset theory, have significantly enhanced the understanding of artificial intelligence adoption behavior. Although the theoretical perspectives offer a robust and generalizable framework, one must keep pace and continuously update their knowledge with the evolution of artificial intelligence landscapes, specifically in the digital era. The model of the study can serve as an intervention for researchers and system developers aiming to accelerate the AIA among students globally. Indeed, the Artificial Intelligence Adoption would ensure inclusive, equitable, and quality educations and thus elevating academic excellence of Malaysian students.

Theoretical and Practical Implications

From a theoretical standpoint, this study confirms the validity of the UTAUT and Mindset Theories in predicting the pattern of students' intention in adopting AI for educational enhancement. Besides this study contributes to the body of knowledge on foreseeing of one's intention to engage with the technology. Additionally, the study also offers practical implications for policymakers, educators, and AI-based educational tool developers in formulating interventions by strengthening all the predicting factors (performance expectancy, effort expectancy, social influence, facilitating conditions and growth mindsets) to accelerate AIA. These factors can significantly increase adoption rates and foster a more engaged and autonomous learning experience.

Limitations and Recommendations for Future Directions

Amidst strengths, the researchers notified several limitations. First, although it offers a cohesive and parsimonious framework with strong explanatory power, the voluntary adoption setting is very complexed to understand, due to uniqueness of human behaviour which is distinct from to another.

Second, this study is conducted in a point of time in Malaysian context, as such it cannot be generalized in other contexts and limit the understanding of the evolution of AI. Future studies are recommended to conduct longitudinal studies to observe changes in behaviour over time, especially as users move from intention to routine use. Future studies are also suggested to conduct cross comparisons research in multiple domains and contact to empirically validate the outcomes in multiple contexts.

Third, the results heavily rely on self-reported intention, which may not likely translate into actual behaviour. Future studies are suggested to interview and observe respondents' behaviour relating to their actual AI adoption. The qualitative insights can disclose meaningful behaviour that could not be revealed by quantitative approaches.

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