The Relationship Between Performance Expectancy, Effort Expectancy, and Perceived Risk on AI Acceptance in Higher Education

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ABSTRACT

The integration of artificial intelligence (AI) in higher education has rapidly expanded, offering potential to enhance student learning, streamline administrative tasks, and personalize educational experiences. However, the acceptance remains uneven due to varying perceptions and student readiness. Despite AI's potential, its implementation faces challenges such as lack of pedagogical integration, perceived complexity, and securities concerns. This study addresses the gap by examining performance expectancy, effort expectancy, and perceived risk that shape student attitudes toward AI in academic contexts. The study examines the relationship of those key factors that influencing AI acceptance in higher education among students at Universiti Teknologi MARA (UiTM), Malaysia. Literature review reveals that student perceptions especially regarding usability and securities are critical in determining AI acceptance. A quantitative research design was employed using a structured questionnaire distributed to 300 students across multiple faculties. Data were analyzed through Pearson correlation and multiple regression. The findings indicate that performance expectancy and effort expectancy significantly influence AI acceptance, with performance expectancy being the most impactful. Regression analysis revealed that perceived risk had no significant effect while low correlated. The result suggest that students are motivated by AI's potential to enhance efficiency and learning outcomes, provided tools that are accessible and institutionally supported. It concludes that fostering a supportive technological environment is key to successful AI acceptance. Recommendations include increasing digital literacy training, ensuring institutional support for AI tools, and addressing privacy and ethical concerns transparently. These efforts can improve user trust and drive meaningful AI adoption in higher education.

Keywords—Performance Expectancy, Effort Expectancy, Perceived Risk, Artificial Intelligence (AI), Higher Education.

INTRODUCTION

Artificial Intelligence (AI) tools have become a part of daily lives. With rapid technological advancement, AI has become an integral part of various fields, including higher education. This integral part is navigated by tools like machine learning, natural language processing (NLP), generative AI and robotics. AI is transforming higher education in terms of learning outcomes, streamline administrative processes and provide students with tailored learning experiences, leading to improved academic performance and engagement [1]. In an optimal scenario, AI would be widely accepted by students and faculty, seamlessly integrated into the educational environment, and contribute positively to the learning experience [2].

AI is not merely integrating in higher education; it is transforming it from the inside out. Academic landscape in current time is rapidly evolving, AI has emerged as a "pedagogical revolution" redefining how knowledge is delivered, accessed, and managed. From automated learning platforms that personalize education to intelligent learning synergy that streamline the task, AI's existence is optimize. AI also bridges the gap between global institutions, enhances inclusivity, and equips students with profound insights to support their academic success.

According to [3], AI significantly affects education. It has the potential to pique students' interest, expedite administrative procedures, and involve them in opportunities for individualized learning. Form academicians' perspectives, AI is pivotal in education as it has the capacity to transform the way that teaching and learning are conducted [4]. Generative AI that utilized deep learning to produce text, images, audio, and other media on its own has help them to manage their tasks more efficiently and provide students more individualized instruction. A study from [5] stated that generative AI-powered chatbot such as Generative Pre-trained Transformers (ChatGPT) are slowly becoming a part of the education ecosystem that students lean on instead of doing research or thinking critically.

Given that AI technologies become more crucial for success in higher education, a captivating paradox has appeared [6]. Varieties of students' perceptions on AI acceptance are encountered. AI integration has the ability to revolutionize teaching strategies, enhance learning possibilities, and encourage independent and self-directed learning in smart education ecosystems. [7] found that integrating AI into discussion boards boosted student participation and encouraged more in-depth interactions. Students felt more comfortable interacting with the chatbots and asking questions in the online classroom, which enhanced their educational prospects and promoted a sense of community.

Ideally, the role of AI, benefits, and students' perceptions all have an impact on how it is viewed and accepted in higher education. While there will be some behavioral changes developed over a period, the potential of AI in higher education extends beyond no exception. As AI becomes increasingly embedded in educational systems, its successful implementation largely depends on the students AI acceptance and the factors that influence it. While some students may embrace AI for its convenience and adaptability, others may be cautious due to concerns about a decline in human interaction or data privacy issues. This gap has prone factors like performance expectancy, effort expectancy, and perceived risk to be fully examined in higher educational settings. These factors can impact whether students and faculty are open to adopting AI, thus affecting its potential to enhance educational outcomes. Without understanding these factors, institutions may struggle to implement AI in a way that is broadly accepted and effective. Hence, this study attempts to examine the relationship of those factors on AI acceptance in higher education.

LITERATURE REVIEW

A number of institutional, technological, and personal variables influence how Artificial Intelligence (AI) is accepted in higher education. Models like the Technology Acceptance Model (TAM) and its expanded forms, including the Unified Theory of Acceptance and Use of Technology (UTAUT), can help to better understand these processes. These frameworks proposed the main factors influencing the use of AI in higher education.

Performance Expectancy

Performance expectancy, which measures consumers' expectations that a technology would improve their performance, strongly predicts technological uptake. In higher education, AI-powered technologies may increase learning efficiency, problem-solving, and academic performance. In the Unified Theory of Acceptance and Use of Technology (UTAUT), [8] defined it as "the degree to which an individual believes that using a system will help them attain gains in job performance." Recently, [9] broadened this concept to emphasize its function in improving learning outcomes and academic productivity with AI technology.

The preparedness and favorable attitude of educators and students toward incorporating AI technologies into learning and administrative operations is called AI acceptance. According to Davis's [10] Technology Acceptance Model (TAM), acceptance is "the willingness of users to employ a technology for the tasks it is designed to support." [11] examined how students and teachers adjust to AI technology in educational contexts, including ease of use, perceived utility, and trust. Performance expectation regularly affects technology adoption, according to research. [8] discovered that people accept technology if they think it would improve performance. [12] found that university students accepted AI-driven learning platforms more when they predicted academic gains. Performance anticipation strongly influences students' intents to utilize AI-based learning management systems, proven by [13], highlighting the strong relationship between projected academic advances and adoption behavior.

Moreover, empirical research has examined performance expectation and how it affects educational technology uptake. [14] found that individualized learning experiences enabled by AI may boost perceived usefulness and student motivation to utilize such technologies. Performance expectation covers motivational and engagement variables as well as academic advantages. After Davis [10] stressed perceived utility as a key component in technology acquisition, following research examined how predicted advantages affect technology adoption. Based on this, [15] demonstrated that performance expectation closely corresponds with students' acceptance of AI-based tutoring systems, suggesting that academic improvements foster favorable views toward AI technology. [16] found that professors are more likely to utilize AI tools if they believe they reduce administrative responsibilities.

Further, [17] noted that faculty adoption of AI technologies depended on their expectations of greater teaching efficiency and student involvement. Performance expectation includes technology capabilities, institutional support, and sufficient training, they said. This argues that organizations promoting AI adoption should foster supportive settings that perpetuate AI's perceived advantages. Technology acceptance models must also examine how performance expectation interacts with social influence and enabling factors. [18] claim that peer and academic leader endorsement may boost performance expectation and AI adoption. When staff and students witness their colleagues using AI, they are more inclined to think it can improve performance. Incorporating performance expectation into institutional initiatives requires demonstrating the technology's capabilities and effect. Workshops, case studies, and success stories help boost AI confidence. Targeted communication initiatives addressing AI myths may also reduce worries and foster academic acceptance. These theoretical and empirical findings underscore performance expectancy's relevance in AI acceptance prediction. Beyond academic benefits, it affects psychological, motivational, and institutional factors. Thus, incorporating AI technology into higher education demands careful consideration to student and instructor performance standards.

H1: There is a significant relationship between performance expectancy and the acceptance of AI in higher education.

Effort Expectancy

Effort Davis [10] defined effort expectancy as the degree to which a person thinks using a system will require little effort. In higher education, this concept helps us understand how students and faculty perceive the user-friendliness and accessibility of AI tools. Meanwhile, ease of use has consistently proven to be a strong predictor of whether people accept new technologies. For example, [8] showed that when users find a system easy to navigate, they are more likely to intend to adopt it. More recently, [19] confirmed this in AI and online learning settings, where ease of use influenced not only attitudes but also perceived usefulness and behavioural intentions [20].

When students find AI platforms, like intelligent tutoring systems, straightforward and requiring minimal training, it reduces mental effort and helps adoption happen more smoothly. [21] found that technologies demanding less effort tend to engage students more effectively. Similarly, [22] reported that AI tutors could speed up learning by about 27%, emphasizing the benefits of easy-to-use systems. For educators, the appeal of AI tools often lies in their simplicity. Features such as automated grading and learning analytics, according to [23], reduce administrative tasks and give teachers more time for creative teaching. This aligns with findings from [24], who noted that when teachers find AI easy to use, they develop more positive attitudes toward it, which in turn supports their willingness to adopt it.

Universities that offer workshops, detailed guides, and live support help build users’ confidence with digital tools. [25] highlight how tailored training programs can lower the perceived difficulty of using AI, regardless of prior experience. Studies on pre-service teachers further underline how digital literacy courses encourage AI adoption [26]. AI tools that assist with grammar checking, content suggestions, or scheduling take over routine tasks, reducing cognitive load and increasing user satisfaction. This creates a positive feedback loop, encouraging continued use and acceptance. However, poorly designed AI systems—those that are hard to install, require constant updates, or have complex interfaces—can become obstacles. This shows why user-centered design, ongoing usability testing, and prompt improvements based on user feedback are essential [27,

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28].

H2: There is a significant relationship between effort expectancy and the acceptance of AI in higher education.

Perceived Risk

Perceived risk is a key factor in understanding how people decide whether to adopt new technologies. [29] explains that it involves the uncertainty and possible negative outcomes tied to a decision. This includes risks inherent to the product or service itself, as well as the challenges users face when making decisions about using it.

[30] defines perceived risk as the combination of how likely an adverse event is to happen and how serious its consequences could be. Typically, researchers measure this through surveys using Likert scales or expectancy-value approaches. More recently, [31] described perceived risk as how individuals perceive both uncertainty and the potential severity of consequences, especially when dealing with technology.

Perceived risk plays a strong role in whether users accept new tech. For instance, [4] found that students' worries about AI misuse or mistakes in educational settings can reduce their willingness to use AI tools. [32] similarly points out that concerns over privacy, financial costs, and AI performance tend to lower users' intentions to adopt these systems. Addressing these fears by promoting transparency, improving security, and designing user-friendly systems is crucial for encouraging acceptance.

This may also apply to studies by [33] that stated the stresses that perceived risks, such as physical, psychological, and financial concern act as significant barriers to adopting AI-powered and robotic technologies. Building trust through secure design and clear, honest communication can go a long way toward increasing user confidence and willingness to engage with AI.

H3: There is a significant relationship between perceived risk and the acceptance of AI in a higher education.

Research Framework

The research framework proposes a direct relationship between three independent variables which is performance expectancy, effort expectancy, and perceived risks. The dependent variable, which is AI acceptance in higher education. It is anticipated that the three independent variables would have an impact on educators and students' readiness to use AI tools in classrooms that affect acceptance of AI. Figure 1 shows the research framework of the relationship.

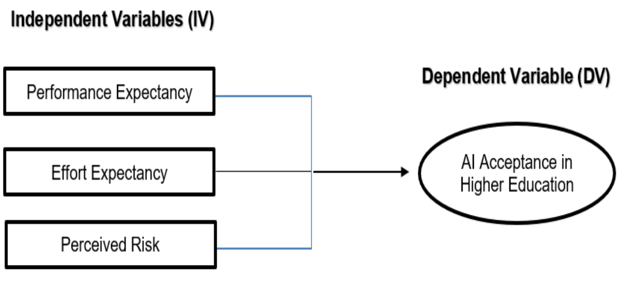

Fig. 1 Research Framework

RESEARCH METHODOLOGY

This study adopts a quantitative, cross-sectional, non-experimental research design to investigate the factors influencing the acceptance of artificial intelligence (AI) technologies in higher education. The research employs a structured questionnaire to collect data from undergraduate students at Universiti Teknologi MARA (UiTM), aiming to evaluate their perceptions, concerns, and willingness to adopt AI tools in academic contexts. A descriptive design was chosen to capture the current state of perceptions without manipulating variables, allowing for statistical generalization and hypothesis testing across a diverse student population.

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Data were collected through a self-administered structured questionnaire disseminated online via Google Forms. This method provided a cost-effective, standardized, and accessible approach, allowing students to complete the survey independently and anonymously. Ethical considerations were strictly followed, with emphasis on voluntary participation, confidentiality, and data protection. The questionnaire consisting of construct-specific items measured on a 7-point Likert Scale which adapted from previous studies to ensure reliability and construct validity. Performance expectancy measurement is adapted from validated measures by [34]. The effort expectancy and perceived risk measurement was modified from validated measures by [35] and [36]. A study on ChatGPT awareness, acceptance, and adoption in higher education by [37] was used as the basis to measure the dependent variable (DV) of AI acceptance in higher education.

Data analysis for this study was conducted using the Statistical Package for the Social Sciences (SPSS) Version 27. Pearson correlation analysis was applied to assess the strength and direction of the linear relationships between the independent variables—namely, performance expectancy, effort expectancy, facilitating conditions, and perceived risk—and the dependent variable, which is AI acceptance in higher education. Following that, multiple regression analysis was conducted to determine the predictive power of the independent variables on the acceptance of AI technology. This analysis allowed for the identification of which factors had statistically significant impacts on students' willingness to adopt AI tools. Finally, Analysis of Variance (ANOVA) was utilized to evaluate the overall fit of the regression model and to confirm whether the model significantly explained variations in the dependent variable. Together, these statistical procedures provided a comprehensive and robust analysis of the data, supporting the study's objectives.

ANALYSIS AND FINDINGS

Correlation Analysis

Correlation analysis measures the correlation between independent variables: performance expectancy, effort expectancy and perceived risk, with AI acceptance in higher education as dependent variable.

TABLE I CORRELATION ANALYSIS

		AI Acceptance	Performance Expectancy	Effort Expectancy	Perceived Risk
AI Acceptance	Pearson Correlation	1	.605**	.549**	.475**
	Sig. (2-tailed)		<.001	<.001	<.001
	N	300	300	300	300
Performance Expectancy	Pearson Correlation	.605**	1	.643**	.537**
	Sig. (2-tailed)	<.001		<.001	<.001
	N	300	300	300	300
Effort Expectancy	Pearson Correlation	.549**	.643**	1	.544**
	Sig. (2-tailed)	<.001	<.001		<.001
	N	300	300	300	300
Perceived Risk	Pearson Correlation	.475**	.537**	.544**	1
	Sig. (2-tailed)	<.001	<.001	<.001	
	N	300	300	300	300

**. Correlation is significant at the 0.01 level (2-tailed).

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Based on the Table 1 above, the Pearson Correlation results indicate a strong significant correlation between performance expectancy and AI acceptance in higher education (r = 0.605). This suggests that an increase in performance expectancy contributes to an increase in AI acceptance in higher education. Meanwhile, the results indicate a moderate significant correlation between effort expectancy and AI acceptance in higher education (r = 0.549). This suggests that an increase in effort expectancy contributes to a moderate increase in AI acceptance in higher education. However, the results indicate a lower significant correlation between perceived risk and AI acceptance in higher education (r = 0.475). This suggests that an increase in perceived risk still has a significant result with AI acceptance in higher education, but with a lower correlation strength compared to the other two independent variables.

In conclusion, all independent variables (performance expectancy, effort expectancy, and perceived risk) have a significant correlation with AI Acceptance in higher education, with strong, moderate, and lower correlation strength. Overall, this means that as these factors increase, the acceptance of AI in higher education is also likely to increase.

Regression Analysis

Regression analysis is a statistical method used to estimate the relationship between a dependent variable and independent variables. In this study on evaluating the perceptions of AI acceptance in higher education among UiTM students, Malaysia, regression analysis was conducted to determine which independent variables significantly influence AI acceptance the most. The three independent variables examined are performance expectancy, effort expectancy, and perceived risk. To evaluate their significance, the Adjusted R-Square value was analyzed, as it indicates the proportion of variance in AI acceptance explained by these factors while considering the number of predictors. A higher Adjusted R-Square suggests that the independent variables play a more significant role in influencing AI acceptance among UiTM students. This analysis helps to understand the key factors contributing to students' acceptance of AI technology in higher education.

TABLE 2 MODEL Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.662[a]	.438	.431	.32511	2.097

Based on Table 2, the model summary shows that R^2 value is 0.438, indicating that 43.8% of the variance in the dependent variable (AI acceptance in higher education) is explained by the independent variables (performance expectancy, effort expectancy, and perceived risk). The Adjusted R-Square value is 0.431, which accounts for the number of predictors in the model and provides a more accurate estimate of the explained variance. This means that 43.1% of the variation in AI acceptance among UiTM students can be attributed to these independent variables. The remaining 56.9% of the variance may be influenced by other factors such as technology awareness, digital literacy, or social influence toward AI acceptance.

The ANOVA regression model results, presented in Table 3, evaluates the overall significance of the model by comparing the variance explained by the independent variables to the variance left unexplained. In this case, the F-value is 57.535, which is relatively high, indicating that the independent variables (performance expectancy, effort expectancy, and perceived risk) collectively explain a significant proportion of the variation in the dependent variable (AI acceptance). Furthermore, the p-value (Sig. < 0.001) is well below the 0.05 significance threshold. This confirms that the regression model is statistically significant, meaning at least one of the independent variables has an impact on the dependent variable.

The ANOVA results further support the model’s robustness. The regression model produced an F-value of 57.535 with degrees of freedom (4, n-5) and the F-value of 57.535 is large, indicating that the variance explained by the model is significantly greater than the unexplained variance. The associated p-value was less than 0.001, well below the conventional 0.05 threshold. This confirms that the model significantly predicts AI acceptance, and the variance explained by the independent variables is significantly greater than the unexplained variance.

Table 3 Anova Regression Model

Source	df	Sum of Squares	Mean Square	F	p-value
Regression	4	SSR	MSR	57.535	0.001
Residual	n - 5	SSE	MSE		
Total	n - 1	SST			

Overall, these findings suggest that the selected predictors play a crucial role in explaining variations in AI acceptance, and the model is a good fit for the data.

Table 4 Regression Analysis Results

Predictor	Coefficient (β)	t-value	p-value	Significance
Performance Expectancy	0.352	5.496	0.050	Significant
Effort Expectancy	0.175	2.580	0.010	Significant
Perceived Risk	0.102	1.833	0.068	Not Significant

Based on Table 4, the regression analysis results, three key variables were examined to determine their significance in shaping the acceptance of AI in academic institutions. These variables include performance expectancy, effort expectancy, and perceived risk. The results indicate that while two of these factors significantly impact AI acceptance, one does not hold substantial influence. Performance expectancy, which refers to the belief that AI will enhance academic efficiency and effectiveness, emerged as a significant factor influencing AI acceptance. The regression analysis revealed a coefficient value of 0.352, a t-value of 5.496, and a p-value of less than 0.050. This demonstrates a strong and statistically significant relationship between beneficial to their academic tasks, they are more likely to adopt it. Consequently, the first hypothesis (H1), which posits a significant relationship between performance expectancy and AI acceptance, is supported by the findings.

Similarly, effort expectancy, which represents the ease of use associated with AI systems, also showed a significant impact on AI acceptance. The regression analysis reported a coefficient of 0.175, a t-value of 2.580, and a p-value of 0.010, which is below the 0.05 threshold. This implies that when AI tools are perceived as user-friendly and easy to integrate into academic activities, their acceptance increases. Hence, the second hypothesis (H2), which suggests a significant relationship between effort expectancy and AI acceptance, is also supported by the analysis.

However, perceived risk, which pertains to the concerns regarding AI usage, such as security, privacy, and potential job displacement, did not show a significant impact on AI acceptance. The regression analysis yielded a coefficient of 0.102, a t-value of 1.833, and a p-value of 0.068, which is greater than 0.05. This suggests that concerns regarding AI risks do not strongly deter individuals from adopting AI in higher education. As a result, the third hypothesis (H3), is not supported by the findings of this study.

The ANOVA results confirm that the overall model significantly explains AI acceptance variability among UiTM students, with performance expectancy and effort expectancy identified as key predictors that highlight the importance of perceived usefulness, ease of use, and support infrastructure in promoting AI adoption. The non-significant effect of perceived risk suggests a relatively low concern or cultural acceptance of AI risks within this group. Although the model accounts for 43.1% of the variance, additional factors such as technology awareness, digital literacy, and social influence should be explored in future research to gain a more comprehensive understanding of AI acceptance in higher education.

DISCUSSION

Results indicate a substantial and significant positive relationship between performance expectations and AI acceptance ($\beta = 0.352$, $t = 5.496$, $p = 0.050$) exceeds the critical value at 5% significance level. A one-unit rise in performance expectation increased AI acceptance probability by 0.352 standard deviation. This shows that students and instructors are more willing to accept AI technology if it improves learning outcomes and efficiency. AI-powered learning platforms, automated grading systems, and intelligent tutoring systems improve academic achievement and administrative operations. AI helped respondents finish tasks faster, improving learning. These supports [8], who found that perceived utility drives technological adoption. The strong relationship indicates that this is the most impactful factor among the three. Consequently, the H1, which posits a significant relationship between performance expectancy and AI acceptance, is supported.

There is also indicate a significant positive relationship between effort expectations and AI acceptance ($\beta = 0.175$, $t = 2.580$, $p = 0.010$). The significance at the 1% level, emphasizing its relevance in higher education AI acceptance. Users that found AI technologies straightforward to use accepted them more. Students utilizing AI-integrated LMSs had little issues. In qualitative replies, several participants said AI tools with simple interfaces lessened their reticence to use the technology. According to [10] Technology Acceptance Model (TAM), simplicity of use is key to technology acceptance. Thus, the H2, which suggests a significant relationship between effort expectancy and AI acceptance, is also supported.

Result indicated that perceived risk, while showing a low coefficient, is not significantly impacts AI acceptance ($\beta = 0.102$, $t = 1.833$, $p = 0.068$) at 5% significance level. The results suggest that although there may be some tendency for increased perceived risk to impact AI acceptance, the coefficient is weak to be considered as statistically significant. While almost students might consider this as a potential contributor, some of them avoid AI technologies due to individual social desirability, trust, data privacy and ethical concerns. Specifically, some UiTM students might be worried about the AI application security, believing their data will be exploited. Academic dishonesty and AI algorithm biases were also identified as adoption hurdles. Previous research has stressed the need of transparency and security in AI applications [38]. Individual trust and acceptance might be improved by stricter data protection regulations, ethical AI techniques, and user awareness campaigns. Nevertheless, with a larger sample, the impact may achieve a substantial result. Hence, the H3, which hypothesizes a significant relationship between perceived risk and AI acceptance in this study, is not supported.

CONCLUSION

The As AI becomes increasingly common in universities, it is important to understand what makes students and educators willing to use these technologies. This study looks at key factors like how useful people think AI is (performance expectancy), how easy it is to use (effort expectancy), and concerns about risks like privacy or ethics (perceived risk). These factors help explain why people might choose to adopt AI tools such as personalized learning platforms, automated grading, or intelligent tutoring systems. This research offers significant information, yet it has numerous drawbacks. The limited sample size may restrict the generalizability of the results to all higher education institutions. The research also focused on a particular academic setting; thus, outcomes may vary by area or institution. Because the research used self-reported data, individuals' replies may be biased or subjective. The fast progress of AI technology may change attitudes and adoption patterns. Future study should address these limitations with bigger sample numbers, longitudinal investigations, and experimental methods.

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