The Influence of Performance Expectancy, Effort Expectancy, and Social Influence on Artificial Intelligence Adoption Behaviour: A Case Study from a Malaysian University

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ABSTRACT

This paper explores the variables that affect the use of Artificial Intelligence among students at the ABC university at Malaysia, based on major constructs of Unified Theory of Acceptance and Use of Technology (UTAUT). The study concentrates on three independent variables, which include the performance expectancy (PE), effort expectancy (EE), and social influence (SE), on Artificial Intelligence (AI) adoption behavior. Data was collected from a sample of 211 students at ABC University via an online questionnaire. The descriptive statistics, reliability test, Spearman correlation were used to analyze the data. Results indicate high levels of internal consistency of all the constructs and high positive associations between each variable and AI adoption behavior. The strongest predictor was effort expectancy, which demonstrates the significance of AI systems that are intuitive and easy to use. The social influence and performance expectancy were also found to play significant roles. Meaning that students are both social-validation- and perceived-academic-benefit-motivated.

Keywords: Artificial Intelligence (AI) Adoption, Unified Theory of Acceptance and Use of Technology (UTAUT), Performance Expectancy, Effort Expectancy, Social Influence

INTRODUCTION

Society has become more technology-driven, especially with the development of new technology. The process of adopting new technology is based on two major factors the first one is the perceived ease of use and the second, the perceived usefulness (Izham, H.I.B, et al., 2025). Among the newest technology that has become popular is artificial intelligence (AI). It has made the lives of people convenient, but at the same time, has gradually interfere with how industries work (Russell et al., 2021; Zhang et al., 2024).

For example, in the education sector, it has lead to a disruptive transformation (Păvăloaia & Necula, 2023). With AI tools, students found real-time support, generate content, summarize reading text, address academic challenges, and engage with data with natural language (Black & Tomlinson, 2025; Vieriu & Petrea, 2025). This has upset the conventional education systems, especially in the tertiary education (Paek & Kim, 2021; Ruano-Borbalan, 2025). Nevertheless, AI tools that are easy to use and readily accessible, are the factors behind its increasing popularity among college students (Ho Ngoc Hai, 2023; Li et al., 2023).

The University of ABC is one of the institutions where students are rapidly incorporating AI into their academic routines. The application of AI-based tools, like ChatGPT, is gaining popularity as students believe that it enhances learning, knowledge, and writing development (Nazari et al., 2021; Nhu et al., 2024). Also, ChatGPT can serve as a fast way to solve problems, meet deadlines and information processing. Moreover, AI applications bring assistance 24/7 and provide opportunity to ask questions that students might feel embarrassed to bring up in the classroom.

In this manner, AI comes in handy for introverted learners especially those whose first language is not English. While these benefits explain why many students are turning to AI, their decision to adopt such tools is also influenced by a variety of personal, social, and institutional factors (Granić, 2023; Strzelecki, 2023; Uzun, 2023; Yakubu et al., 2025). The ethical frameworks established by the technology developers (OpenAI, 2024) and institutional concerns over academic integrity (Cornell University, 2023) further shape the adoption environment.

Problem Statement and Research Gap

ABC is a university where a large population of local and international students are enrolled. Thus, the dynamics of AI adoption might be different compared to those in Western universities (Faraon et al., 2025). Nonetheless, little empirical data has been found regarding the perceptions of performance expectancy, effort expectancy, and social influence in the adoption of AI among Malaysian students (He et al., 2024; Ruslan, 2024; Yakubu et al., 2025).

This paper aims to close this gap by analyzing the behavioral and contextual variables that can determine the adoption of AI by ABC university students. Consequently, it also contributes to academic literature as well as practical solutions to higher education institutions in Malaysia. Based on the preceding paragraphs, the following are the research objectives and research questions of this study.

Research Objectives (RO)

RO1: To analyze the influence of performance expectancy on Artificial Intelligence adoption behavior among University of ABC students.

RO2: To analyze the influence of effort expectancy on Artificial Intelligence adoption behavior among University of ABC students.

RO3: To analyze the influence of social influence on Artificial Intelligence adoption behavior among University of ABC students.

Significant of Study

The significance of this study is to offer customized insights that reflect the unique social, cultural, and institutional realities of Malaysian universities. It can examine the roles of performance expectancy, effort expectancy, and social influence in predicting AI adoption behavior among ABC university students,

LITERATURE REVIEW

This section draws upon well-known model frameworks, the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze and provide evidence for the dependent and independent variables in the research. To demonstrate the theoretical and practical significance of each component, this paper will review previously published research findings. This leads to the formulation of research hypotheses and the suggested study framework.

Identification and Conceptualization of Variables

AI Adoption Behavior (DV)

AI Adoption Behavior (AAB) refers to the degree to which college students use AI technology in their academic or personal lives to provide them with information, generate content, or answer questions (Nhu et al., 2024). As example, students use ChatGPT to write outline and add requirements and guidance for assignments or projects. In doing so, they believe they get the most suitable answer (Sánchez-Prieto et al., 2020; Chong et al., 2022; Wen et al.,2024).

Past studies suggest that students who use AI for writing and research are more satisfied and productive than those who did not use AI (Nazari et al., 2021). The impact of AAB is also related to the usage environment. AI is more suitable for highly repetitive work or time-consuming tasks such as complex data processing or large volume translations (Holmes et al., 2021; Zhang et al., 2024).

Furthermore, AI has gained popularity among students because they leverage this powerful tool. However, how much students utilize the tool depend on their feelings about its worth, usefulness, and dependability (Cunningham, 1967; Chong et al., 2022; Bloomfield & Rushby, 2024). This link between perceived risk, satisfaction, and behavioral intention is a recognized concept in literature (Tran, 2020).

Performance Expectancy (IV1)

Performance expectancy may be perceived as how useful technology can be in working or studying as perceived by people (Merz et al., 2025) It is grounded in Unified Theory of Acceptance and Use of Technology (UTAUT) and conceptually aligned with perceived usefulness in Technology Acceptance Model (TAM) (Davis, 1989), and very much related to perceived utility (Hoo et al., 2023).

According to Mustafa and Garcia, (2021) the literature has indicated that performance expectancy is one of the central variables in adopting and final usage of information systems where high-performance expectancy creates more acceptability by a user in adopting the new technology (Jain et al., 2022). According to Sewandono et al. (2022), performance expectancy is the evaluation of how individuals believe in technology will be for their professions or educations.

Effort Expectancy (IV2)

Effort Expectancy (EE) refers to the ease or difficulty of using a particular technology (Du & Beibei Lv, 2024), especially when first using any new technology (Du & Beibei Lv, 2024). Venkatesh et al. (2003) proposed this concept in the Unified Theory of Acceptance and Use of Technology (UTAUT) and pointed out that one of the four core determinants that affect users' willingness to use new technologies is Effort Expectancy. This concept is similar to the perceived ease of use in the Technology Acceptance Model (TAM), where users prefer to accept technologies that they think are easier to use and understand (Li et al., 2023).

Social Influence (IV3)

Social influence in this study refers to the phenomenon where an individual's thoughts, behaviors, and decisions gradually conform to or follow the patterns of the general public in order to adapt to societal norms (Spears, 2021). This theory is particularly applicable to the factors influencing students' adoption of AI in this study. During their learning process, students are inevitably exposed to their teachers, classmates, and even the educational system, all of which generally have their own rules.

According to Guassi Moreira et al., (2021), when these groups' thoughts and behaviors align, students' choices can be influenced. Essiz & Mandrik (2021) also point out that family and friends are one of the most important sources of information in the consumer decision-making process, which also proves that students' decision-making judgments are influenced by the values of their family and friends.

To further illustrate social influence, this study found that Alessandro Rovetta et al. (2025) also indicate that people tend to accept culture, values, and social identity of their social group and adjust their behavior accordingly. This suggests that when people's decisions are disapproved by the public, their decisions will gradually change to conform to the public's direction, which is similar to social identity theory (Tajfel & Turner, (1979).

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Conceptual Framework

This study examines the relationship between AI Adoption Behavior (AAB) and three key factors derived from the UTAUT model: Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI). Based on the literature review and underpinning theory, the following is the theoretical framework for this study.

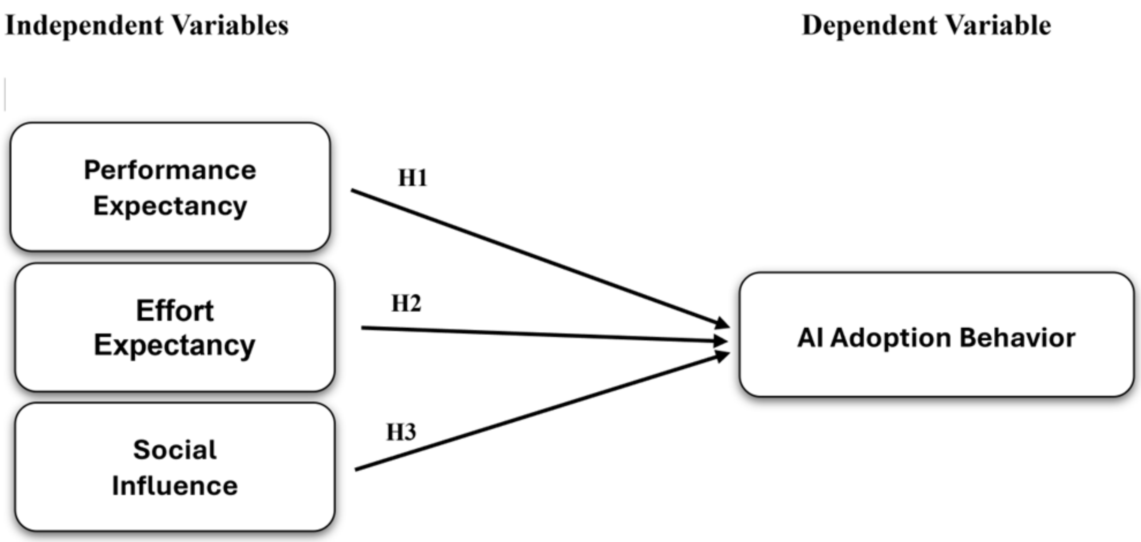

Figure 1 Conceptual Framework

Hypothesis Formulation

Relationship between Performance Expectancy and AI Adoption Behavior

Performance Expectancy (PE) can be described as a degree to which the students suppose that utilization of AI can help them to improve their academic results (Moradi, 2025). Previous research has consistently shown that PE and technology adoption have a positive correlation (Sewandono et al., 2022; Yakubu et al., 2025).

As an example, students are likely to use AI tools when they see apparent scholarly advantages like better writing or more rapid access to information. Nonetheless, there is some research which indicates the strength of such a relationship is not constant in different contexts; in the contexts where students do not trust AI-generated information, PE might have a more modest impact on adoption intention (Li et al., 2023; Safdar et al., 2024; Kiat et al., 2025;). Since the context of higher education in Malaysia is unique, the key research question can be tested by whether PE has a significant impact on the usage of AI tools by students ABC university.

H1: Performance Expectancy has a positive relationship with AI adoption behavior among ABC university students.

Relationship between Effort Expectancy and AI Adoption Behavior.

Effort Expectancy (EE) is the ease of using AI tools in studying. Past research attests to the fact that students tend to use technologies that are simple in nature (Venkatesh et al., 2003). Even in the example of ChatGPT, its conversational interface enables even non-technical students to interact with AI, which also makes it adoptable (Strzelecki, 2023).

However, certain studies show that in the case of younger and more technologically savvy groups, the impact of EE is not as strong, since students assume that most tools should be easy to use (Li et al., 2023). This is where an issue emerges whether EE plays significant role in adoption in the university setting like ABC university which have students that are already familiar with digital platforms.

H2: Expectancy has a positive relationship with AI adoption behavior among ABC university students.

Relationship between Social Influence and AI Adoption Behavior.

Social influence refers to the influence of friends, family, classmates, and other important people who frequently interact with each other about use of AI technology. When this happen, it will also enhance a person's view on the use of this technology (Cheng et al., 2022; Jain et al., 2022). Studies have shown that people tend to follow the technology choices of those around them to meet social expectations, so social expectations will greatly affect individual technology use behavior (Ruslan, 2024; Merz et al., 2025).

For example, if someone is around a person who is willing to accept AI technology, then there is a likelihood they can influence each other to use the technology. On the contrary, if culture of a certain art college is to support original design, then they are likely to be influenced by the college not using AI technology as their own creative content (Kraatz & Xie, 2023).

H3: Social influence has a significant positive relationship with AI adoption behavior among ABC university students.

METHODOLOGY

This study employed a quantitative research approach (Hunziker & Blankenagel, 2024) grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate the factors influencing AI adoption behavior among students. A sample of 211 undergraduate and postgraduate students from a single university was obtained via an online questionnaire using a non-probability convenience sampling method (Andrade, 2021; Rahman, 2023). The data collection ensured ethical standards, including informed consent and voluntary participation (Millum & Bromwich, 2021; Mumford, Higgs, & Gujar, 2021; Hansaram & Munap, 2025).

The instrument measured the independent variable which are Performance Expectancy, Effort Expectancy, and Social Influence and the dependent variable, AI Adoption Behavior. The survey used a five-point Likert scale (Mohd Rokeman, 2024). Data were analyzed using SPSS version 29 (Pallant, 2020), employing descriptive statistics, reliability analysis (Cronbach, 1951; Hair et al., 2019), and Spearman correlation (Shapiro & Wilk, 1965) to examine relationships between the constructs at a significance level of $p < 0.05$.

RESULTS AND DISCUSSIONS

This section presents the analysis of the survey data collected to investigate the factors influencing AI adoption behavior among students. The findings are structured as follows: demographic profile of respondents, assessment of measurement reliability, descriptive statistics of the constructs, correlation analysis, and hypothesis testing.

Demographic Profile of Respondents

Table 4.1 Demographic profile

Demographic Characteristic	Category	Frequency(n)	Percentage (%)
Gender	Female	125	59.20%
	Male	86	40.80%
	Total	**211**	**100.00%**
Age	20–22 years old	137	64.90%
	23–25 years old	34	16.10%

	Above 25 years old	12	5.70%
	Below 20 years old	28	13.30%
	Total	**211**	**100.00%**
Programme of study	Bachelor's Degree	100	47.4
	Diploma	69	32.7
	Foundation	22	10.4
	Postgraduate	20	9.5
	Total	**211**	**100.00%**
Main purpose of Using ChatGPT	Academic writing / assignments	44	20.9
	Entertainment / casual use	14	6.6
	Idea generation / brainstorming	74	35.1
	Learning / understanding difficult topics	37	17.5
	Translation or language practice	42	19.9
	Total	211	100

From table 4.1, the online survey yielded 237 responses, of which 211 were valid and complete, resulting in a high response rate of 89.11%. This sample size of 211 exceeds the recommended minimum ratio of 10:1 (respondents to items) for statistical reliability, given the 18 measurement items used in the study (Memon et al., 2020; Hair et al., 2021). The demographic analysis reveals a diverse respondent profile. The sample comprised slightly more females (59.2%) than males (40.8%). In terms of age, most respondents (64.9%) were between 20 and 22 years old. Academically, bachelor's degree students formed the largest group (47.4%), followed by Diploma (32.7%), Foundation (10.4%), and Postgraduate (9.5%) students.

The field of study was well-distributed, with the largest cohorts from Communication/Media (30.8%) and Business/Management/Marketing (26.5%). Regarding the primary purpose of using ChatGPT, the most common reason was idea generation and brainstorming (35.1%), followed by academic writing/assignments (20.9%) and translation/language practice (19.9%), indicating a predominant use for educational and productive tasks (Black & Tomlinson, 2025).

4.2 Reliability Analysis

Table 4.2 Reliability Analysis (Cronbach's Alpha)

Variable	**Cronbach's Alpha Value**	**No. of items**
Performance Expectancy	0.848	6
Effort Expectancy	0.869	6
Social Influence	0.857	6
AI Adoption Behavior	0.784	6

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The internal consistency of the measurement scales was assessed using Cronbach's Alpha (Cronbach, 1951). As shown in Table 4.2, all constructs demonstrated high reliability, with values exceeding the accepted threshold of 0.7 (Hair et al., 2019). The independent variables: Performance Expectancy ($\alpha = 0.848$), Effort Expectancy ($\alpha = 0.869$), and Social Influence ($\alpha = 0.857$) and the dependent variable, AI Adoption Behavior ($\alpha = 0.784$), all exhibited good to excellent reliability, confirming the instrument's internal consistency.

Descriptive Statistics of Constructs

Table 4.3 Descriptive Statistics

Code	**Item**	**Sample size(n)**	**Mean**	**Standard Deviation**
Performance Expectancy (PE)				
PE1	Using ChatGPT in my job/assignment would enable me to accomplish tasks more quickly.	211	4.2	1.038
PE2	Using ChatGPT would improve my academic performance.	211	3.83	1.125
PE3	Using ChatGPT for my job would increase my productivity.	211	4.15	1.043
PE4	Using ChatGPT would enhance my effectiveness on my job.	211	3.93	0.993
PE5	Using ChatGPT would make it easier to do my job.	211	4.06	1.074
PE6	I would find ChatGPT useful in my job.	211	4.03	1.028
Effort Expectancy				
EE1	Learning to operate ChatGPT would be easy for me.	211	4.18	1.034
EE2	I would find it easy to get ChatGPT to do what I want it to do.	211	3.93	1.033
EE3	My interaction with ChatGPT would be clear and understandable.	211	3.92	1.174
EE4	I would find ChatGPT to be flexible to interact with.	211	4.01	1.067
EE5	It would be easy for me to become skilful by using ChatGPT.	211	3.96	0.999
EE6	I would find ChatGPT easy to use.	211	3.87	1.134
Social Influence				
SI1	People I care about encourage me to use ChatGPT.	211	3.97	1.062
SI2	Most people surrounding me use ChatGPT.	211	3.88	1.097
SI3	My lecturers' opinions influence my decision to use ChatGPT.	211	3.73	1.261
SI4	People who influence me encourage me to use ChatGPT.	211	3.8	1.064
SI5	The university environment creates pressure for me to adopt ChatGPT in learning.	211	3.91	1.083
SI6	Using ChatGPT is viewed positively by people whose opinions I value.	211	3.79	1.17
AI Adoption Behavior				

AAB1	I will continue to acquire ChatGPT related information.	211	4.07	1.117
AAB2	I will keep myself updated with the latest ChatGPT applications.	211	3.89	1.153
AAB3	I intend to use ChatGPT to assist with my learning.	211	4.14	0.959
AAB4	I will continue to learn ChatGPT.	211	4.11	1.025
AAB5	I frequently use ChatGPT to complete academic-related tasks.	211	4.12	0.983
AAB6	I plan to integrate ChatGPT into my long-term study routine.	211	4.45	0.817

The descriptive statistics for the key constructs revealed consistently positive perceptions among respondents. For Performance Expectancy (PE), the mean scores for the individual items ranged from 3.83 to 4.20 on a 5-point scale. The strongest agreement was with the statement, "Using ChatGPT would enable me to accomplish tasks more quickly" (*M*=4.20, *SD*=1.038), underscoring the tool's perceived role in enhancing efficiency (Sewandono et al., 2022).

Similarly, for Effort Expectancy (EE), mean scores fell between 3.87 and 4.18, with the highest score attributed to "Learning to operate ChatGPT would be easy for me" (*M*=4.18, *SD*=1.034), indicating a consensus on the platform's learnability (Li et al., 2023). The Social Influence (SI) construct, while displaying slightly lower mean scores from 3.73 to 3.97, still reflected a positive social environment, with the strongest influence coming from close peers as captured by the item, "People I care about encourage me to use ChatGPT" (*M*=3.97, *SD*=1.062) (Spears, 2021).

Finally, the dependent variable, AI Adoption Behavior (AAB), demonstrated the most robust results, with all items exceeding 3.89. The highest level of agreement was found for the intention, "I plan to integrate ChatGPT into my long-term study routine" (*M*=4.45, *SD*=0.817), signaling a strong commitment to the tool's continued use (Holzmann et al., 2025).

Normality Test Result

Table 4.4 Normality Test

Variables	**Kolmogorov-Smirnov[a]**			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Performance Expectancy	0.230	211	<.001	0.875	211	<.001
Effort Expectancy	0.293	211	<.001	0.849	211	<.001
Social Influence	0.285	211	<.001	0.838	211	<.001
AI Adoption Behavior	0.213	211	<.001	0.864	211	<.001
a. Lilliefors Significance Correction						

To assess the distribution of the data, normality tests were conducted. The Shapiro-Wilk test indicated a significant deviation from normality for all constructs ($p < .001$), as shown in Table 4. Consequently, non-parametric statistical methods, specifically Spearman's rank-order correlation, were employed for the subsequent inferential analysis to ensure robust and valid findings (Shapiro & Wilk, 1965; Mat Roni & Djajadikerta, 2021).

Correlation Analysis

Table 4.5 Correlation analysis

Variables			*Performance* Expectancy	*Effort* Expectancy	*Social* Influence	*AI Adoption* Behavior
Spearman's rho	Performance Expectancy	Correlation Coefficient	1	.797**	.761**	.750**
		Sig. (2-tailed)	.	<.001	<.001	<.001
		N	211	211	211	211
	Effort Expectancy	Correlation Coefficient	.797**	1	.757**	.770**
		Sig. (2-tailed)	<.001	.	<.001	<.001
		N	211	211	211	211
	Social Influence	Correlation Coefficient	.761**	.757**	1	.725**
		Sig. (2-tailed)	<.001	<.001	.	<.001
		N	211	211	211	211
	AI Adoption Behavior	Correlation Coefficient	.750**	.770**	.725**	1
		Sig. (2-tailed)	<.001	<.001	<.001	.
		N	211	211	211	211
**. Correlation is significant at the 0.01 level (2-tailed).						

Spearman's rank-order correlation was used to examine the relationships between the independent variables (PE, EE, SI) and the dependent variable (AAB). The results, summarized in Table 4.5, reveal significant positive correlations between all three independent variables and AI Adoption Behavior (Jain et al., 2022).

Specifically, AI Adoption Behavior has a strong positive correlation with Effort Expectancy ($\rho = 0.770$, $p < .001$), followed by Performance Expectancy ($\rho = 0.750$, $p < .001$) and Social Influence ($\rho = 0.725$, $p < .001$). Furthermore, the independent variables were also highly correlated with each other, with the correlation between PE and EE ($\rho = 0.797$) indicating potential multicollinearity, which should be diagnosed in future regression analyses.

Hypothesis Testing

Table 4.6 Hypothesis Testing Results

Hypothesis	**Description**	**Correlation Coefficient (ρ)**	**p-value**	**Result**
H1	There is a significant positive relationship between Performance Expectancy and AI Adoption Behavior.	0.75	< 0.001	**Accepted**

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H2	There is a significant positive relationship between Effort Expectancy and AI Adoption Behavior.	0.77	< 0.001	**Accepted**
H3	There is a significant positive relationship between Social Influence and AI Adoption Behavior.	0.725	< 0.001	**Accepted**

The study proposed three hypotheses to test the positive relationship between the independent variables and AI Adoption Behavior. The results of the Spearman correlation analysis, presented in Table 4.6, led to the acceptance of all three hypotheses. The findings confirm that students' adoption of AI tools like ChatGPT is significantly influenced by their perception of its performance benefits (PE), ease of use (EE), and the social pressures and norms surrounding its use (SI) (Jain et al., 2022).

The analysis provides robust evidence that Performance Expectancy, Effort Expectancy, and Social Influence are significant determinants of AI Adoption Behavior among university students. The measurement instrument proved reliable, and all hypothesized relationships were strongly supported. The high inter-correlations among the independent variables suggest a intertwined perception of the tool's usefulness, ease of use, and social acceptance. These findings offer valuable insights for educators and institutions seeking to foster the productive adoption of AI in educational contexts.

CONCLUSION

This section focuses on discussion that reveals the study's research findings. The primary objective is to hypothesize the results and assess them in light of the study objectives and questions. Specifically, is to examine how Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) influence AI Adoption Behavior (AAB) among students at ABC University, Malaysia.

Beyond interpreting the key results, the study also highlights the theoretical and practical implications of the findings, discusses the limitations encountered in the research process, and offers recommendations for future studies. By doing so, it provide a clearer understanding of the factors shaping students’ intention to use ChatGPT, as well as guidance for educators, institutions, and researchers who intend to explore AI adoption in higher education.

DISCUSSION OF FINDINGS

This section is an inquiry into how the research findings are interpreted, how the statistical results are connected to the research questions and the underlying UTAUT framework (Venkatesh et al., 2003). This discussion will provide the reasons as to why the identified relationships between Performance Expectancy, Effort Expectancy, Social Influence, and AI Adoption Behavior are present, by putting them into perspective in existing literature.

Relationship between Performance Expectancy and AI Adoption Behavior

The results of the analysis affirm that there is strong positive correlation between performance expectancy and the behavior of AI adoption among students in ABC university. This result means that the students who hold the opinion that the application of AI tools such as ChatGPT will render them positive academic benefits are much more prone to the integration of this technology into their learning activities. Close relationship demonstrates the power of perceived utility as one of the main factors of technology acceptance (Davis, 1989).

This finding is closely related to the central principles of the UTAUT model and is backed by the current studies in the field of educational AI. An example of this is that in a study by Yakubu et al. (2025) on the use of generative AI to learn, the performance expectancy was the best predictor of behavioral intention. Their investigation concluded that students are encouraged to embrace AI when they believe that it provides them with a direct tool to improve their performance and output in scholarly institutions, which is the direct finding that aligns with the findings of this paper.

Further support comes from Moradi (2025), who investigated ChatGPT acceptance among Chinese university students. In the study, the perceived usefulness of AI on enhancing learning outcomes came out as a crucial issue that affected adoption, which agreed with the findings of the ABC university students. Thus, the findings of this paper, in line with the literature, prove that the instrumental value of AI in promoting academic efficacy is a crucial factor that predetermines its application in higher education.

Relationship between Effort Expectancy and AI Adoption Behavior

The research develops a positive strong correlation between the expectancy of effort and the adoption behavior of AI. It means that the convenience of using AI tools is one of the key facilitators of their adoption. As soon as students discover AI applications such as ChatGPT to be user-friendly, clear, and easy to interact with, their chances to use them will rise significantly.

This discovery is a fundamental pillar of technology acceptance models, and it is strongly supported by the recent empirical research on the use of AI in education. In his research on the acceptability of ChatGPT to students, Strzelecki (2023) discovered that the expectancy of effort was a significant predictor of the intention to use the technology and actual use. He has conducted research that underlines the fact that low learning curve and the intuitive interface of such tools are critical in their quick acceptance of the tools by the students into their workflow.

Similarly, Holzmann et al. (2025) investigated the generative AI continuous use determinants in students. Their results emphasized that perceived ease of use was a key to the continuation of engagement, meaning that when students do not think that the technology is easy to use, the initial interest in using it might not be converted into sustained adoption. These studies interconnecting with the current findings serve to emphasize the importance of reducing perceived complexity as a key to promoting the popular and long-term adoption of AI tools in the academic environment.

Relationship between Social Influence and AI Adoption Behavior

The findings support the existence of a positive substantial relationship between social influence and the adoption behavior of AI. This shows that the attitudes and actions of key referent groups, including peers, lecturers, and the university community at large have a significant influence on whether students will use AI or not. The social environment is an important source of normative pressure and information, which will lessen uncertainty about a new technology (Tajfel & Turner, 1979).

Current literature confirms this result highly. In an international exploratory study, Faraon et al. (2025) revealed that social influence was a key predictor of the intention of students to use ChatGPT in various countries. They observed that the students tend to embrace AI when they perceive that individuals who are significant to them ought to use it.

Moreover, another study by Cheng et al. (2022) on AI implementation, albeit in the healthcare environment, offers a solid theoretical support. They showed that social influence, which can be provided by peers and superiors, has a significant positive effect on the intention to adopt AI-assisted systems, which indicates the universal impact of social networks on technological diffusion. As such, this paper confirms that the utility and ease assessment of adopting AI is not only an individual, but it is also firmly rooted in a social environment in which the perception and support of one group are a significant factor.

This study acknowledges key limitations that is, its findings are not broadly generalizable due to a geographically restricted sample from one Malaysian university and a convenience sampling method that may introduce bias. The reliance on self-reported survey data also posed another limitations that it created risks on social desirability bias, thus, potentially inflating reports of AI adoption and positive perceptions. Furthermore, the cross-sectional design captures only a snapshot in time, preventing causal conclusions or insight into evolving behaviors. Finally, the research focused only on core facilitators from the UTAUT model. In this manner, it omits potential barriers like academic integrity concerns, data privacy, and over-reliance, which future studies should incorporate for a more balanced understanding.

In order to overcome the limitations of the study, future research should adopt longitudinal designs to track evolving AI usage and establish causality. At the same time the research should integrate mixed methods to enrich self-reported data with qualitative depth. In addition, the theoretical model must be expanded to include factors like perceived risks, institutional support, and ethical considerations where other analysis techniques like SEM is used. Finally, studies should be replicated across diverse institutions, disciplines, and cultural contexts to significantly improve the generalizability and robustness of findings on AI adoption in higher education.

To sum up, this research paper has verified that the usage of AI tools by the ABC university population is largely determined by Performance Expectancy, Effort Expectancy, and Social Influence, as the UTAUT model proposes (Li et al., 2023). The high positive correlations of all three hypotheses highlight the fact that the students tend to adopt AI more when they find it useful, easy to use, and socially acceptable.

The results provide theoretical support of the UTAUT model within a modern educational setting and practical recommendations on how universities should be guided. In the case of ABC university and other similar universities, it is important to show the academic potential of AI strategically, make it easy to use, and create a friendly social atmosphere to encourage responsible use. Although this work is limited due to its scope and methodology, it offers a critical framework of future studies and practicable action on the changing AI situation in higher education (Su et al., 2025). These recommendations must align with evolving ethical standards and institutional policies to ensure responsible integration of AI.

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Conflict Of Interest

The authors declare no conflicts of interest.

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