

Embracing AI in Higher Education: What Drives Students' Intention to Use Artificial Intelligence?

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DOI: <https://doi.org/10.47772/IJRISS.2026.100801175>

Received: 09 September 2026; Accepted: 14 September 2026; Published: 26 September 2026

ABSTRACT

Artificial Intelligence (AI) is increasingly embedded in university learning, but access to AI does not necessarily translate into students' intention to use it for academic purposes. This study examined whether performance expectancy, effort expectancy, social influence, and facilitating conditions are associated with undergraduate students' behavioural intention to use AI at Universiti Teknologi MARA (UiTM). The study was guided by the Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative cross-sectional survey was conducted using convenience sampling. Of 202 responses received, 178 valid responses remained after screening for eligibility, straightlining and potential outliers. Data were analysed using IBM SPSS Statistics through descriptive statistics, reliability analysis, a marker-variable assessment, Pearson correlation and multiple regression. Accordingly, the high explanatory power of the model should be interpreted as reflecting substantial shared variance among the UTAUT predictors rather than four clearly separable independent effects. The findings provide contextual evidence on AI acceptance among UiTM undergraduates and indicate that perceived academic value remains particularly important.

Keywords: Artificial Intelligence, Behavioural Intention, UTAUT, Performance Expectancy, Effort Expectancy

INTRODUCTION

Artificial Intelligence (AI) has become an increasingly visible part of university learning. Students use AI-based tools to search for information, understand difficult topics, generate ideas, improve writing, obtain feedback, and support other academic activities. International evidence indicates that AI use among university students is already widespread, while recent studies continue to document growing adoption of generative AI in higher education (Digital Education Council, 2024; Sergeeva et al., 2025). This growing use creates an important distinction between access to AI and intention to use it. Students may have access to the same technologies but differ in whether they perceive them as useful, easy to use, socially acceptable, and adequately supported.

Technology acceptance research provides a useful basis for examining these differences. The Unified Theory of Acceptance and Use of Technology (UTAUT) identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as important technology-related beliefs and conditions (Venkatesh et al., 2003). In the original UTAUT model, performance expectancy, effort expectancy and social influence are linked to behavioural intention, whereas facilitating conditions are primarily associated with use behaviour. However, recent studies of AI adoption have also examined facilitating conditions as a direct predictor of behavioural intention, with mixed findings (Sergeeva et al., 2025; Xu et al., 2025; Yakubu et al., 2025).

The Malaysian higher education context warrants specific attention because students' experiences with AI may differ across institutions, programmes, levels of digital exposure and forms of institutional guidance. Malaysian studies have examined AI-based academic support, ChatGPT adoption, AI integration and AI

literacy, but the dependent variables, samples and model specifications differ across studies (Dahri et al., 2024; Foroughi et al., 2025; Siddiqui et al., 2025; Yusnilzahri et al., 2025). Consequently, there remains a need for context-specific evidence on how the four selected UTAUT factors operate together in explaining behavioural intention among UiTM undergraduate students.

The present study addresses this contextual and model-specification gap by examining the joint and unique contributions of performance expectancy, effort expectancy, social influence and facilitating conditions to behavioural intention to use AI. Rather than claiming a new theoretical model, the study provides empirical evidence on an adapted application of UTAUT to AI use in a Malaysian public-university setting. The study also identifies which predictor makes the strongest contribution when the four factors are entered simultaneously.

Research Questions and Objectives

The study addresses the following five research questions:

- RQ1: What is the relationship between performance expectancy and undergraduate students' behavioural intention to use AI at UiTM?
- RQ2: What is the relationship between effort expectancy and undergraduate students' behavioural intention to use AI at UiTM?
- RQ3: What is the relationship between social influence and undergraduate students' behavioural intention to use AI at UiTM?
- RQ4: What is the relationship between facilitating conditions and undergraduate students' behavioural intention to use AI at UiTM?
- RQ5: Which of the four UTAUT factors makes the strongest unique contribution to behavioural intention to use AI at UiTM?

LITERATURE REVIEW

Unified Theory of Acceptance and Use of Technology

UTAUT was developed to integrate key determinants of technology acceptance across several established models (Venkatesh et al., 2003). Performance expectancy reflects the degree to which an individual believes that using technology will help achieve gains in performance. Effort expectancy refers to the perceived ease associated with using technology, while social influence concerns the extent to which important others influence an individual's decision to use it. Facilitating conditions refer to the resources and support available for technology use. These constructs are relevant to university students because AI adoption involves judgments about academic usefulness, usability, social expectations and access to support.

The present study uses an adapted UTAUT framework. Facilitating conditions are examined as a direct predictor of behavioural intention rather than only as an antecedent of actual use. This specification is consistent with recent AI adoption studies that have explored facilitating conditions as an intention-related factor (Sergeeva et al., 2025; Xu et al., 2025; Yakubu et al., 2025). The original UTAUT moderators are not examined because the study focuses on the four selected predictors and their direct relationships with behavioural intention.

Behavioural Intention to Use Artificial Intelligence

Behavioural intention refers to an individual's willingness or readiness to perform a particular behaviour. Within the UTAUT framework, it represents the extent to which an individual intends to use technology and is an important precursor to actual technology use (Venkatesh et al., 2003). In this study, behavioural intention refers to undergraduate students' willingness to use Artificial Intelligence (AI) tools for academic activities. Recent UTAUT-based studies in higher education similarly position behavioural intention as a key outcome of AI adoption, although the strength of its predictors may vary across contexts (Siddiqui et al., 2025; Yakubu et al., 2025).

Behavioural intention should also be distinguished from actual technology use, as students may have a strong intention to use AI but encounter barriers such as limited support, unclear institutional guidance, or concerns about acceptable academic use. Yakubu et al. (2025), for example, found that performance expectancy, effort expectancy and social influence significantly predicted students' intention to use content-generative AI, whereas facilitating conditions were not significant. Therefore, the present study focuses on behavioural intention as the dependent variable and examines the roles of performance expectancy, effort expectancy, social influence and facilitating conditions in shaping students' intention to use AI.

Performance Expectancy and Behavioural Intention

Performance expectancy is the belief that technology will improve task performance. For students, this may involve using AI to understand course materials, completing academic tasks more efficiently, generating ideas or improving the quality of learning activities. Evidence from recent higher education studies generally indicates that perceived usefulness or performance benefits are important in students' intention to adopt AI and ChatGPT (Dahri et al., 2024; Siddiqui et al., 2025; Xu et al., 2025). Therefore, students who perceive clear academic benefits from AI are expected to report stronger behavioural intention.

H1: Performance expectancy has a significant positive relationship with undergraduate students' behavioural intention to use AI.

Effort Expectancy and Behavioural Intention

Effort expectancy concerns the perceived ease of learning and operating a technology. AI tools that use natural-language interaction may reduce the technical effort required to begin using them. Prior studies have reported positive relationships between ease of use and AI acceptance in higher education, including Malaysian settings (Dahri et al., 2024; Yahaya et al., 2024; Yakubu et al., 2025). However, some evidence suggests that ease of use may become less important as users gain experience with technology. Testing the relationship in a UiTM sample therefore remains relevant.

H2: Effort expectancy has a significant positive relationship with undergraduate students' behavioural intention to use AI.

Social Influence and Behavioural Intention

Social influence refers to the perceived influence of people who are important to the student, such as friends and lecturers. Students may become more willing to use AI when they observe peers using it or when lecturers communicate that its use is appropriate for particular academic activities. Recent studies have reported significant effects of social influence in some student populations, while others have found weaker relationships (Korchak et al., 2025; Siddiqui et al., 2025; Ursavaş et al., 2025). These mixed findings suggest that social influence may depend on the student group and learning environment.

H3: Social influence has a significant positive relationship with undergraduate students' behavioural intention to use AI.

Facilitating Conditions and Behavioural Intention

Facilitating conditions encompass the resources, infrastructure, technical support and guidance available to enable technology use. In higher education, these conditions may include access to devices and internet connectivity, technical assistance, training and institutional guidance on acceptable AI use. Although facilitating conditions were originally positioned primarily as a determinant of use behaviour in UTAUT, recent AI studies have examined their direct relationship with behavioural intention and reported inconsistent findings (Sergeeva et al., 2025; Xu et al., 2025; Yakubu et al., 2025). This provides a rationale for testing the relationship in the UiTM context.

H4: Facilitating conditions have a significant positive relationship with undergraduate students' behavioural intention to use AI.

METHODOLOGY

Research Design and Participants

A quantitative, non-experimental, cross-sectional survey design was employed. The target population comprised UiTM undergraduate students who had experience using at least one AI-based tool for academic or learning purposes. Convenience sampling was used because a complete and accessible sampling frame of all UiTM undergraduate students was not available. The questionnaire was distributed online through WhatsApp and other accessible academic and peer networks, with lecturers, friends and students assisting in reaching eligible respondents. The unit of analysis was the individual undergraduate student.

A total of 202 responses were received. Screening removed two ineligible responses, 18 straightlining responses and four potential outliers, resulting in 178 valid cases for analysis. The final sample exceeded the minimum requirement estimated through G*Power for multiple regression with four predictors (Cohen, 1992) and Green (1991) guideline of $N \geq 50 + 8m$, which gives 82 cases for four predictors. The study therefore had an adequate sample size for the planned regression analysis.

Measures

The questionnaire comprised demographic questions and measurement items for performance expectancy, effort expectancy, social influence, facilitating conditions and behavioural intention to use AI. The four UTAUT predictors were adapted from Baca & Zhushi (2025), with minor wording adjustments for AI use in higher education. The adaptation focused on contextualizing the original wording to students' academic use of AI while retaining the conceptual meaning of each UTAUT construct. No new theoretical dimensions were introduced. The wording was reviewed for relevance to the higher-education context before administration. However, a formal item-level assessment of convergent and discriminant validity was not conducted in the present study, and this is acknowledged as a measurement limitation. Behavioural intention items were adapted primarily from Venkatesh et al. (2003) and contextualised to academic AI use. All substantive constructs were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Performance expectancy was measured with four items; effort expectancy, social influence and facilitating conditions with three items each; and behavioural intention with four items. One social influence item, SI03, contained wording that referred directly to respondents' intention to use AI. Although the item was retained as part of the original three-item social influence measure used in this study, its wording may create conceptual overlap with the behavioural intention construct. This potential overlap is therefore acknowledged as a measurement limitation and is taken into account when interpreting the social influence coefficient in the regression analysis.

Two environmental-responsibility items were included as a marker variable to assess possible common method bias. The marker items were: (1) "I believe that environmental protection is everyone's responsibility" and (2) "I try to reduce waste in my daily life." The marker variable was theoretically unrelated to AI acceptance and was used only for methodological assessment, following the marker-variable approach described by Lindell & Whitney (2001) and Podsakoff et al. (2003).

Data Collection and Analysis

Before the main survey, a pilot test involving 49 valid respondents was conducted. Pilot reliability was acceptable overall, although effort expectancy ($\alpha = .674$) and facilitating conditions ($\alpha = .654$) were slightly below .70 and were reviewed before the main study. The main data were analysed using IBM SPSS Statistics. Descriptive statistics were used to summarise respondent characteristics and construct responses. Cronbach's

alpha assessed internal consistency. Pearson correlation examined bivariate associations, while multiple regression assessed the unique contribution of the four predictors to behavioural intention.

Regression assumptions were also examined, including independence of errors, linearity, homoscedasticity, normality of residuals, multicollinearity and influential cases. Multicollinearity was assessed using tolerance and variance inflation factor (VIF) statistics. Because all variables were collected through one self-report questionnaire, a theoretically unrelated marker variable was also examined to assess possible common method bias.

RESULTS

Respondent Profile

The final sample consisted of 178 UiTM undergraduate students. Females represented 52.2% of the sample and males 47.8%. Most respondents were aged 20–22 years (64.0%), followed by 23–25 years (31.5%). The largest faculty group was Computer Science and Mathematics (22.5%), followed by Accounting (17.4%) and Business and Management (15.2%). Students from all eight study parts were represented, with Part 1 forming the largest group (28.1%). All respondents had previous experience using an AI-based educational tool. In terms of familiarity, 48.9% reported being very familiar with AI and 24.7% familiar, indicating that 73.6% were at least familiar with AI in education.

Because respondents could select more than one AI tool, percentages do not sum to 100%. ChatGPT or similar chatbots were the most frequently reported tools (84.3%), followed by AI-based recommendation systems (73.6%), auto-grading or writing tools (60.1%), and intelligent tutoring systems (54.5%).

Descriptive Statistics and Reliability

All constructs recorded means above the midpoint of the five-point scale, indicating generally positive perceptions of AI use. Performance expectancy had the highest mean ($M = 4.0295$), while social influence was the lowest ($M = 3.8446$). All Cronbach's alpha values exceeded .70, ranging from .765 to .907, indicating acceptable internal consistency for the main study measures. The results are shown in Table 1.

Table 1. Descriptive Statistics and Internal Consistency

Construct	N	Mean	SD	Cronbach's α
Performance Expectancy	178	4.0295	0.9445	0.907
Effort Expectancy	178	3.9682	0.8427	0.765
Social Influence	178	3.8446	0.9897	0.859
Facilitating Conditions	178	3.9082	0.9670	0.829
Behavioural Intention	178	3.9733	0.9265	0.889

Common Method Assessment and Multicollinearity

The two marker-variable items were strongly correlated with each other ($r = .722$, $p < .001$). Unexpectedly, the marker variable also correlated strongly with the substantive constructs, with correlations ranging from .703 to .852. This pattern indicates that the marker did not function as a clearly unrelated methodological variable. Although the four substantive predictors remained statistically significant after controlling for the marker and the marker itself was not significant in the regression model, these results cannot be interpreted as evidence that common method bias was absent. Rather, the strong correlations between the marker and

substantive constructs reduce the diagnostic value of the marker-variable procedure. Common method variance therefore remains a plausible alternative explanation for part of the covariance observed among the study variables. The results are shown in Table 2.

Table 2. Multicollinearity Diagnostics

Predictor	Tolerance	VIF	Interpretation
Performance Expectancy	.129	7.727	Substantial overlap
Effort Expectancy	.195	5.123	Substantial overlap
Social Influence	.098	10.206	Above 10; high concern
Facilitating Conditions	.136	7.353	Substantial overlap

The magnitude of the VIF statistics indicates that the regression coefficients are estimated in the presence of substantial predictor overlap. Consequently, the statistical significance of an individual coefficient should not be interpreted as evidence that the corresponding construct has a large independent effect. Multicollinearity inflates coefficient uncertainty and makes the relative magnitude and ordering of the standardised coefficients sensitive to shared variance among the predictors.

The regression results are therefore interpreted primarily as evidence that the four UTAUT-related measures jointly account for substantial variance in behavioural intention, while conclusions regarding their distinct individual contributions remain tentative.

Regression Results and Hypothesis Testing

The multiple regression model was statistically significant, $F(4, 173) = 421.133$, $p < .001$, and explained 90.7% of the variance in behavioural intention ($R^2 = .907$; adjusted $R^2 = .905$). Performance expectancy showed the largest standardised coefficient ($\beta = .386$, $p < .001$), followed by effort expectancy ($\beta = .241$, $p < .001$), social influence ($\beta = .234$, $p = .002$), and facilitating conditions ($\beta = .132$, $p = .038$). Accordingly, H1, H2, H3 and H4 were supported. These hypothesis decisions reflect statistically significant associations within the fitted regression model and should not be interpreted as evidence of independent causal effects.

The high R^2 should nevertheless be interpreted cautiously. The unusually strong correlations among the predictors, VIF values above 5, the direct wording of SI03 in relation to intention, and the marker-variable results suggest that some of the apparent explanatory power may reflect shared measurement variance. In addition, residual normality was not fully satisfied. The findings therefore demonstrate strong sample-specific explanatory power rather than causal evidence or proof that the four constructs operate independently. Table 3 below shows the regression coefficients and hypothesis decisions.

Table 3. Regression Coefficients and Hypothesis Decisions

Predictor	Unstandardized Coefficient (B)	Standard Error	β	t	p	95% Confidence Interval for B	Semi-partial Correlation	Unique Variance Explained
Performance Expectancy	.378	.063	.386	5.980	< .001	[.253, .503]	.139	.019

Effort Expectancy	.265	.058	.241	4.590	< .001	[.151, .379]	.106	.011
Social Influence	.219	.069	.234	3.158	.002	[.082, .356]	.073	.005
Facilitating Conditions	.126	.060	.132	2.093	.038	[.007, .245]	.049	.002

The multiple regression model was statistically significant, $F(4, 173) = 421.133$, $p < .001$, explaining 90.7% of the variance in behavioural intention ($R^2 = .907$, adjusted $R^2 = .905$). Performance expectancy showed the largest standardised coefficient ($B = .378$, $SE = .063$, $\beta = .386$, 95% CI [.253, .503], $p < .001$), followed by effort expectancy ($B = .265$, $SE = .058$, $\beta = .241$, 95% CI [.151, .379], $p < .001$), social influence ($B = .219$, $SE = .069$, $\beta = .234$, 95% CI [.082, .356], $p = .002$), and facilitating conditions ($B = .126$, $SE = .060$, $\beta = .132$, 95% CI [.007, .245], $p = .038$).

However, the semi-partial correlations indicate that the unique contribution of each predictor was considerably smaller than the overall model R^2 . Performance expectancy uniquely accounted for approximately 1.93% of the variance in behavioural intention, followed by effort expectancy at 1.12%, social influence at 0.53%, and facilitating conditions at 0.24%. These findings indicate that a substantial proportion of the model's explained variance was shared among the highly correlated predictors. Therefore, the relative magnitude of the regression coefficients should be interpreted cautiously rather than as evidence of clearly independent effects.

DISCUSSION

RQ1: Performance Expectancy and Behavioural Intention

RQ1 examined whether performance expectancy was related to behavioural intention. Performance expectancy produced the largest standardised regression coefficient in the full model ($\beta = .386$, $p < .001$). This finding is consistent with UTAUT and with recent studies showing that students are more likely to adopt AI when they perceive clear academic benefits (Siddiqui et al., 2025; Xu et al., 2025). The result is also understandable because all respondents had prior AI experience, meaning that students were evaluating a technology they had already encountered rather than an unfamiliar system. In practical terms, the finding indicates that students' intention to use AI was positively associated with their perception of its usefulness for learning, academic tasks, and performance. However, because performance expectancy was strongly correlated with the other predictors, the coefficient should be interpreted as the largest conditional association within the present regression model rather than definitive evidence that performance expectancy is independently more influential than the other UTAUT factors.

RQ2: Effort Expectancy and Behavioural Intention

RQ2 examined the relationships of effort expectancy and behavioural. Effort expectancy was positively associated with behavioural intention ($\beta = .241$, $p < .001$). This is consistent with evidence that ease of use can support students' acceptance of AI-based tools (Dahri et al., 2024; Yahaya et al., 2024; Yakubu et al., 2025). AI interfaces that allow natural-language interaction may reduce the initial technical barrier and make experimentation easier for students from different academic disciplines. Although effort expectancy was weaker than performance expectancy, the result indicates that usability remains relevant even among students who already have experience with AI.

RQ3: Social Influence and Behavioural Intention

RQ3 examined the relationship between social influence and behavioural intention. Social influence was positively associated with behavioural intention ($\beta = .234$, $p = .002$), consistent with studies reporting that

peers, lecturers and social norms can shape students' intention to use generative AI (Korchak et al., 2025; Siddiqui et al., 2025). The finding suggests that AI use may be influenced not only by individual evaluations of usefulness but also by signals from the surrounding academic environment.

However, this result requires caution. Social influence recorded the highest VIF (10.206), and SI03 explicitly referred to the respondent's intention to use AI. Although SI03 was retained because it contributed to the planned three-item construct and improved internal consistency, its wording creates some conceptual overlap with behavioural intention. The positive association should therefore be interpreted as evidence of a relationship within the present sample rather than as a precise estimate of a distinct social influence effect.

This measurement overlap is particularly important because behavioural intention is the dependent variable in the present study. An item within the social influence scale that directly refers to intention may artificially strengthen the observed association between social influence and behavioural intention. Consequently, the social influence coefficient may partly reflect similarity in item wording rather than a fully distinct social influence effect. This issue should therefore be considered when interpreting the magnitude and significance of the social influence coefficient.

RQ4: Facilitating Conditions

RQ4 examined the relationship between facilitating conditions and behavioural intention. Facilitating conditions had the smallest but still statistically significant coefficient ($\beta = .132$, $p = .038$). This finding indicates that access to devices and internet connectivity, technical support and university guidance were positively associated with behavioural intention. It is noteworthy because facilitating conditions were originally positioned primarily as a determinant of use behaviour in UTAUT (Venkatesh et al., 2003). The present result is nevertheless compatible with recent AI studies that have examined facilitating conditions in relation to intention and reported mixed findings (Sergeeva et al., 2025; Xu et al., 2025; Yakubu et al., 2025). One possible interpretation is that students consider institutional guidance and available support when deciding whether they are comfortable continuing to use AI for academic work.

IMPLICATIONS

Theoretical Implications

The findings provide contextual support for the relevance of the selected UTAUT dimensions to students' behavioural intention to use AI, consistent with prior research applying UTAUT and related technology-acceptance perspectives in higher education (Venkatesh et al., 2003; Siddiqui et al., 2025; Yakubu et al., 2025). However, the very high correlations among performance expectancy, effort expectancy, social influence, and facilitating conditions in the present study suggest that these dimensions may not have been fully differentiated in the current measurement context. Therefore, the findings should not be interpreted as evidence that the four constructs represent clearly independent mechanisms underlying students' behavioural intention to use AI.

The finding for facilitating conditions should also be interpreted within the adapted specification of UTAUT used in this study. In the original UTAUT framework, facilitating conditions were primarily proposed as a determinant of use behaviour rather than behavioural intention (Venkatesh et al., 2003). Recent studies of AI adoption, however, have also examined facilitating conditions as a direct predictor of behavioural intention, with mixed findings across contexts (Sergeeva et al., 2025; Xu et al., 2025; Yakubu et al., 2025). Its statistically significant association with behavioural intention in the present study therefore provides context-specific evidence for an adapted application of UTAUT rather than a theoretical revision of the original model. This distinction is important because the present cross-sectional design cannot establish whether facilitating conditions directly produce stronger behavioural intention.

More broadly, the substantial shared variance among the predictors highlights the importance of establishing discriminant validity before drawing strong conclusions about their relative theoretical importance. Future

research should therefore assess whether performance expectancy, effort expectancy, social influence, and facilitating conditions remain empirically distinct when applied to students' academic use of AI. Confirmatory factor analysis or structural equation modelling may provide a stronger basis for evaluating the measurement structure and the relationships among these constructs.

Practical Implications

For UiTM and similar institutions, a practical implication of the observed association with performance expectancy is that institutions may consider making the academic value and limitations of AI more explicit to students. Lecturers and institutional support units can provide examples showing how AI can assist with brainstorming, understanding difficult concepts, research planning, revision and early drafting while emphasising verification and academic integrity. Practical AI-literacy training should be concise and task-oriented, covering prompt formulation, source checking, privacy and appropriate acknowledgement of AI use.

The observed association between social influence and behavioural intention indicates that lecturers and peers may form part of the social context surrounding students' decisions about AI use. However, because the study is cross-sectional, the finding does not establish that changing social influence would cause stronger behavioural intention. Rather than promoting unrestricted AI use, they can clarify when AI is appropriate, demonstrate responsible use and reinforce the importance of students' own judgement. Finally, facilitating conditions should include accessible guidance, technical support and clear course-level policies so that students know what forms of AI use are permitted.

LIMITATIONS AND FUTURE RESEARCH

Several limitations should be considered. First, convenience sampling means that the sample was not statistically representative of all UiTM undergraduate students. Some faculties and student groups may have been more accessible than others, and students with greater interest in AI may have been more willing to participate. Second, cross-sectional design captures perceptions at one point in time and cannot establish temporal or causal relationships. Third, all substantive variables were collected using the same self-report questionnaire. The marker-variable assessment did not clearly eliminate the possibility of common method bias.

Fourth, the predictors were highly intercorrelated and the VIF values ranged from 5.123 to 10.206. This reduces confidence in interpreting the exact unique contribution of each predictor. The wording of SI03 also creates some overlap with behavioural intention. The high correlations and VIF values also suggest that a substantial proportion of the explained variance may be shared among the predictors. Therefore, the high R^2 of .907 should be interpreted cautiously and should not be taken to mean that each predictor provides a clearly independent contribution to behavioural intention. In addition, the present study did not re-estimate the regression model after removing SI03. Future research should therefore conduct sensitivity analysis by excluding potentially overlapping items such as SI03 to determine whether the regression coefficients, multicollinearity diagnostics, and overall model results remain stable. Finally, residual normality was not fully satisfied.

Future research should employ probability-based or stratified sampling across faculties, campuses, and study levels to improve the representativeness and generalisability of the findings. Longitudinal designs should also be considered to examine changes in students' behavioural intention over time. Future studies should also include actual AI-use measures, such as frequency of use or task-specific use, rather than relying only on behavioural intention. In addition, item-level assessments of convergent and discriminant validity should be conducted to determine whether the four UTAUT constructs are sufficiently distinct. Confirmatory factor analysis or structural equation modelling may help assess this issue. Sensitivity analyses should also be conducted by removing items with potential conceptual overlap, particularly SI03, to examine whether the regression coefficients, multicollinearity diagnostics, and overall model results remain stable. Future models may also examine additional constructs such as AI literacy, trust, perceived risk, habit, and actual use behaviour where theoretically justified.

CONCLUSION

This study examined four UTAUT factors associated with undergraduate students' behavioural intention to use AI at UiTM. Performance expectancy, effort expectancy, social influence and facilitating conditions were all positively associated with behavioural intention, with performance expectancy showing the largest standardised coefficient. However, because the predictors were highly intercorrelated, the relative magnitude of these coefficients should not be interpreted as a definitive ranking of their theoretical importance. The findings suggest that students are more willing to use AI when they perceive clear academic benefits, find the technology easy to use, observe supportive social signals and have access to relevant resources and guidance.

The study also demonstrates why the results should be interpreted in context. The high R^2 , substantial multicollinearity, possible common method bias and one item with wording overlap limit the confidence that can be placed in the exact independent effect of each predictor. Accordingly, the principal contribution of the study is contextual rather than causal. The findings indicate that the selected UTAUT-related measures are strongly associated with AI-use intention among the participating UiTM undergraduates. However, the substantial shared variance among the predictors indicates that stronger measurement validation is required before their independent theoretical contributions can be established.

Ethical Considerations

Ethical approval was obtained from the Faculty Research Ethics Committee (FERC), Faculty of Business and Management, Universiti Teknologi MARA, under reference FERC/FBM/MR/2025511057. The study was approved as minimum-risk research. Participation was voluntary and based on digital informed consent. The questionnaire did not request student identification numbers, home addresses or telephone numbers, and responses were treated confidentially and used only for academic purposes.

Data Availability

The underlying respondent-level dataset is not publicly available because it contains research participant information and is subject to confidentiality protections.

Conflict of Interest

The author declares no conflict of interest related to this article.

ACKNOWLEDGEMENTS

The authors acknowledge the support of Universiti Teknologi MARA and the undergraduate students who participated in the study.

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