

Understanding Behavioral Intention of AI Adoption: A Conceptual Framework Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) Model

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ABSTRACT

The twenty-first century brought Artificial Intelligence (AI) as a revolutionary technology which now transforms multiple sectors including business operations, educational systems, financial services and medical care delivery. While there are many positive impacts for student learning through Artificial Intelligence (AI), student usage and adoption of AI systems at higher education institutions continues to be variable. Student use of AI can be limited as a result of student perceptions about the reliability of AI systems, their own privacy when using AI, ethical concerns associated with the design and operation of AI systems, and perceived technical difficulties with AI. In addition, the literature on factors affecting student adoption of technology-based tools (such as AI systems) has presented contradictory evidence about which specific variables drive adoption behavior among students. Moreover, the literature provides little context about the nature of higher education institutions (HEI) in Malaysia and the applicability of those studies to institutions in Malaysia. This paper addresses the lack of empirical and contextual information on student adoption of technology-based tools such as AI systems by proposing a theoretical framework based upon an adaptation of the Unified Theory of Acceptance and Use of Technology (UTAUT). The proposed research defines how four fundamental predictors performance expectancy, effort expectancy, social influence, and facilitating conditions collectively impact the undergraduate students' intentions to use AI. Unlike prior studies focused upon empirical tests of theories related to technology acceptance, this conceptual paper theoretically integrates current literature into a single, coherent framework along with testable hypotheses. From both theoretical and practical perspectives, the expected contributions of this study include providing a common basis from which to resolve the contradictions found in literature concerning the drivers of student adoption of AI by reassessing the original UTAUT constructs. Additionally, the proposed framework should provide the structured knowledge base necessary for higher education institution administrators, educators, and policymakers to create targeted strategies for integrating AI systems across all levels of institutional operations. Ultimately, future empirical testing of this framework should provide Malaysian HEIs with actionable data that may facilitate the development of explicit academic integrity guidelines; refinement of assessment designs; and creation of targeted AI literacy programs.

INTRODUCTION

The twenty-first century brought AI as a revolutionary technology which brought major changes to multiple fields including healthcare and business and finance and manufacturing and education (Brandao, 2025). The AI technology breakthroughs in generative AI technology brought about a transformation in how people interact with information while creating ideas, solving problems and developing solutions through platforms such as ChatGPT and Google Gemini and Microsoft Copilot and Grammarly and many others. The higher education sector experienced technological breakthroughs which introduced multiple educational solutions that allowed students to access individualized learning experiences while receiving immediate feedback and scientists could enhance their work productivity and students gained simple access

to educational materials (Gruenbichler et al., 2024). The new technological advances allow students to learn better while their academic results improve and they develop digital skills which will help them succeed in the fast-changing workplace environment. Despite the growing availability and potential benefits of AI technologies, students' acceptance and usage of AI applications vary considerably. While many students readily adopt AI-powered tools to support assignments, research activities, writing, programming, and problem-solving tasks, others remain hesitant due to concerns regarding information accuracy, trustworthiness, privacy, data security, ethical implications, academic integrity, limited AI literacy, and the perceived complexity of these technologies (Kasneci et al., 2023; UNESCO, 2023). Such differences in acceptance suggest that technological advancement alone does not guarantee successful adoption. Instead, students' perceptions, beliefs, and readiness to use AI significantly influence their willingness to integrate these technologies into their academic activities. Therefore, understanding the factors that influence students' behavioural intention to use AI is essential for promoting its effective, ethical, and responsible adoption among students in HEI.

LITERATURE REVIEW

Behavioural intention is extensively acknowledged as a significant predictor of actual technology usage, as individuals with a heightened desire to utilise a technology are typically more inclined to accept and persist in its use (Ajzen, 1991; Venkatesh et al., 2003). To explain users' acceptance of emerging technologies, several theoretical models have been developed, including the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), the Value-Based Adoption Model (VAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT). Among these, the UTAUT model has been extensively validated across diverse technological contexts and is regarded as one of the most comprehensive frameworks for predicting technology adoption. The model proposes that performance expectancy, effort expectancy, social influence, and facilitating conditions are the primary determinants influencing users' behavioural intention and actual technology use (Venkatesh et al., 2003). UTAUT offers a suitable theoretical framework for investigating the elements influencing students' behavioural intention to utilise AI, given the growing use of AI technology in higher education.

AI has becoming more popular in education due to its potential to transform teaching and learning processes. AI technologies provide various educational benefits which include customized learning approaches and improved information availability and enhanced academic output and support for decision-making processes and problem resolution (Lo et al., 2024; Dwivedi et al., 2021). The educational sector use AI applications which include intelligent learning systems and generative AI to help students with their academic work and their research activities and their content development and their school participation. As a result, behavioural intention has become a significant variable to determine the readiness of students to use AI in their learning process.

The potential of artificial intelligence to improve learning results at educational institutions through its ability to boost academic performance and creative thinking and information access faces multiple operational challenges during its integration process. Issues relating to academic integrity, algorithmic bias, transparency, ethical decision-making, overreliance on AI-generated content, and the potential decline of students' critical thinking skills have become significant concerns among educators and researchers (Kasneci et al., 2023; UNESCO, 2023). Consequently, HEI needs to establish a proper balance between AI educational advantages and their management through ethical standards, digital competence programs and correct organizational oversight. Educational institutions need to create evidence-based strategies which support proper AI usage while students learn effectively, keep their academic integrity, develop better critical thinking and problem-solving abilities through understanding what affects their choice to use AI. Global higher education has completely changed as a result of the quick development of generative artificial intelligence (GenAI) technology. HEIs are now faced with the reality of near-universal incorporation into everyday academic routines rather than assessing whether students will accept these technologies. Globally, empirical data highlights this shift; for instance, the Higher Education Policy Institute reported that 95% of undergraduate students have utilized AI in some capacity, with 94% explicitly leveraging generative AI to support assessed coursework (Stephenson & Armstrong, 2026). In parallel, a

global audit by Turnitin (2024) analyzing over 200 million academic papers revealed that 11% (over 22 million submissions) contained at least 20% AI-generated content.

The global expansion of AI technology has become standard practice for all academic institutions which Malaysian universities follow through their student population who use AI for their assignments and research work and creative thinking activities (Mohsin, 2025). The fast growth of academic assistance has surpassed established rules which makes students confused about the correct limits between authorized help and dishonest work and plagiarism (Mohsin, 2025). AI brings multiple advantages to academic settings through its ability to boost technological advancement and enhance student learning outcomes and generate more research results and speed up complex information retrieval. The excessive use of generative tools creates a risk which could harm students' ability to perform independent critical thinking while it damages their capacity for advanced problem-solving and it threatens the established principles of academic honesty (Blahopoulou & Ortiz-Bonnin, 2025; Abubakar et al., 2025). Higher education institutions are therefore faced with an operational challenge: they must create an atmosphere that promotes the ethical and successful deployment of AI to produce graduates who are prepared for the digital age while also reducing the dangers of academic misconduct and over-reliance. Universities urgently need empirical data on the precise elements influencing students' behavioural intention to use AI responsibly in order to develop focused institutional policies and pedagogical interventions. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) serves as a foundational theoretical framework to explain technology adoption through four core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Although UTAUT has been extensively deployed in educational contexts, a critical analysis of current literature reveals three key research gaps:

Firstly, existing research studies present conflicting results about which original UTAUT elements function as the main factors which shape student behavioral choices for AI usage. Foroughi et al. (2023) conducted research which showed that Performance Expectancy stands as the most powerful factor which leads students to adopt AI because they mainly focus on usefulness. Tang et al. (2025) discovered that Social Influence together with Habit behavior had more impact than direct utility assessment. Research studies about Facilitating Conditions show extreme differences in their results because Yacob et al. (2025) found a strong positive link to behavioral intention yet Du & Lv (2024) discovered no statistical relationship. The existing conflicting research results demonstrate scientists have not reached an agreement about the fundamental elements which drive AI adoption.

Secondly, people adopt technology through their actions which get limited by their cultural background and the social framework and technological systems which exist in their environment. The research conducted by Zhao et al. (2025) demonstrated that student populations across national borders (e.g., Malaysian vs. Chinese university students) show distinct patterns when students use generative AI technology during their academic work. Consequently, lack of contextual findings derived from Western or non-Malaysian contexts fail to show how they affect public universities in Malaysia because these institutions operate with their own specific administrative systems and cultural practices.

Thirdly, recent academic trends have favored complex extended models (e.g., UTAUT2 incorporating constructs such as hedonic motivation, price value, or AI literacy). However, this push toward model extension has fragmented baseline metrics. The original four-construct UTAUT model needs theoretical backup to prove its ability to predict results and explain patterns when used with generative AI in Malaysian public universities.

Accordingly, this study seeks to address the identified empirical, contextual, and theoretical gaps by examining the influence of the factors on undergraduate students' behavioural intention to use Artificial Intelligence at Universiti Teknologi MARA (UiTM) Shah Alam. The findings are expected to contribute to the technology acceptance literature by providing empirical evidence on the applicability of the original UTAUT framework in explaining AI adoption within the Malaysian higher education context.

PROPOSED METHODOLOGY

This theoretical study provides a conceptual model to investigate factors affecting the decision to adopt Artificial Intelligence (AI) by undergraduate students. For further research, this section identifies a proposed methodology (research design, sampling strategy, measurement instrument construction, ethics, and statistical analyses) to test the hypothesized relations based upon the conceptual model and the hypotheses (H1–H4).

Research Design and Setting

The proposed study employs an explanatory design using a cross sectional survey approach. A cross sectional survey is suitable to identify associations between independent (non-manipulated), operationally defined variables measured at one point in time; it is also very commonly used as a methodological choice in studies about technology acceptance. In terms of the sample population and setting, the proposed study utilizes Universiti Teknologi MARA (UiTM) Shah Alam, Malaysia as the empirical setting, but restricts itself to all undergraduate students studying at UiTM who have either utilized Generative AI for their academic assignments and or have had access to Generative AI tools (ChatGPT, Google Gemini, Copilot).

Sampling Strategy and Sample Size

Purposive sampling will be employed as a non probability sampling technique. Purposive sampling can be justifiable for two main reasons. First, respondents need to have previously experienced or been exposed to some form of AI application(s) as part of their Higher Education (HE) activities (for example: researching, completing assignments, coding). Second, there needs to be evidence that respondents are able to articulate their beliefs about performance expectancy, effort expectancy, social influence, and facilitating conditions. Screening questions at the start of the questionnaire will be used to determine whether potential respondents meet the inclusion criteria of being current undergraduate students at UiTM before they begin answering the items contained within the questionnaire.

The sample size needed to establish adequate statistical power as well as generalizability was determined by a combination of factors: (1) Statistical Power Analysis (G*Power 3.1): Based on a multiple regression model with four major predictor variables ($m=4$), $\alpha=0.05$, a standard statistical power of $1 - \beta = 0.80$, and a medium-sized effect ($f^2 = 0.15$), a total sample size of $N = 85$ is needed. Next is Green's (1991) Formula of Thumb: Using Green's formula for testing the adequacy of the overall model ($N \geq 50 + 8m$), which has m as the number of predictor variables ($m = 4$), a total of $N \geq 82$ participants are needed for testing the overall model. Testing each individual predictor variable requires at least $N \geq 104 + m$ or a total of $N = 108$ participants. For this study, the practical target in order to provide for potentially lost data due to missing values in response questions, possible non-response biases as well as potential violation of multivariate normality assumptions of many distributions, the study is planning to survey a large enough sample size that would have a range of $N = 200$ to $N = 300$ undergraduate students from the various UiTM Shah Alam faculties. The targeted sample size will exceed the minimal amounts, while providing sufficient statistical power for either regression analysis or structural equation modeling (SEM).

Instrument Development

The survey instrument consists of two parts which are Section A is about Demographics (age, gender, faculty, year of study, how frequently you use an AI tool.) Section B will measure the theoretical concepts developed in this research project using a 5-point Likert scale (1-"Strongly Disagree", 5-"Strongly Agree"). All items were derived from existing valid instruments found within the technology acceptance literature (Venkatesh et al., 2003) and have been modified to fit the context of AI adoption into Higher Education.

Construct	Code	Adapted Source	Operational Definition in AI Context
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Performance Expectancy	PE	Venkatesh et al. (2003)	Degree to which a student believes using AI will enhance academic productivity and learning outcomes.
Effort Expectancy	EE	Venkatesh et al. (2003)	Degree of ease associated with learning and using AI applications.
Social Influence	SI	Venkatesh et al. (2003)	Degree to which a student perceives that peers, lecturers, and institution influence their AI usage.
Facilitating Conditions	FC	Venkatesh et al. (2003)	Degree to which a student believes institutional/technological infrastructure exists to support AI use.
Behavioral Intention	BI	Venkatesh et al. (2003)	Student's explicit intention to continue adopting AI tools for academic tasks.

Data Collection Methodology

To ensure the reliability of data collected will conduct a three-step validation process before collecting all of the data.

1. **Content and Face Validity:** A panel of two educational technologist or Information System expert will review and critique our adopted instrument to determine the clarity of each item, its relevance to the current context as well as whether they are consistent with the original UTAUT construct.
2. **Pilot study and pre-testing** will be executed to validate instrument on a sample size of N=30 to N=50 undergraduate students. Internal Consistency will be measured by Cronbach's Alpha (α). If at least one of the subscales has an internal consistency value of $\alpha \geq 0.70$, then those subscale(s) will be discarded.
3. **Construct validity and reliability:** In addition to assessing the internal consistency during our main data collection, there will also assess the convergent validity and discriminant validity through establishing composite reliability values greater than 0.70, average variance extracted (AVE) values greater than 0.50. Lastly, this study will assess discrimination validity through the Fornell Larcker criteria as well as the HTMT ratio.

Ethical Procedure

Institutional policies will be followed to maintain ethical procedures as follows:

Consent: Respondents are provided a clearly stated Information Sheet describing the research goals; that this is non-commercial; and that they have the right to withdraw at their discretion from participating in this study.

Anonymity and Confidentiality: None of respondents' identifiable details (i.e. e.g. Student ID #s, Full Names, IP addresses, etc.) will be collected or documented. All data collected will be compiled for purposes of statistical analysis.

Protection of Data: The electronic responses received will be encrypted. These electronic responses will also be stored securely according to regulations under Malaysia's Personal Data Protection Act (PDPA).

Data Analytical Strategy

The empirical data from this study will be analyzed by using partial least squares structural equation modeling (PLS SEM) through the use of SmartPLS. This methodological approach is particularly appropriate to this study because PLS SEM is well-suited for the analysis of complex models that contain

latent variables and does not need to have data that are normally distributed. The measurement model of the developed model will be initially assessed based on an established two-stage analytical process in order to assess both the internal consistency reliability, convergent validity and discriminant validity. Internal consistency reliabilities will be measured when composite reliabilities are greater than 0.7, and average variance extracted values are greater than 0.5. Discriminant validities will also be tested when heterotrait-monotrait (htmt) ratios are less than .85. In addition, once the measurement model has been validated, the structural model will then be assessed using a bootstrap technique that will create five thousand sub samples to verify the hypothesized relationships (H1-H4).

CONCEPTUAL FRAMEWORK

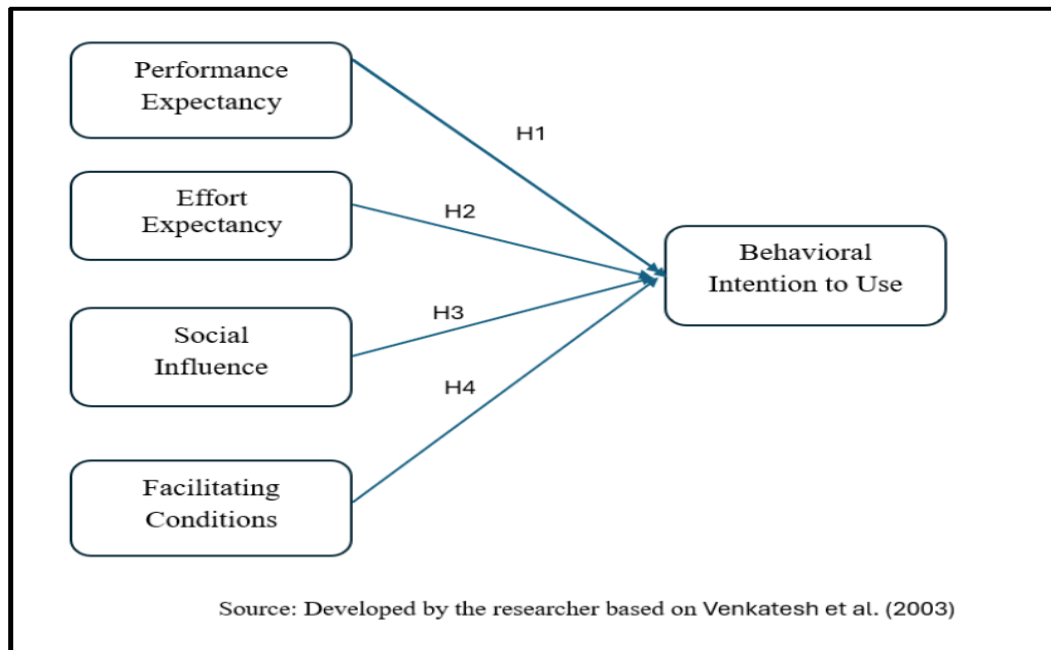


Figure 1.0 Conceptual Framework

UTAUT was chosen as it offers a detailed model to explain the acceptance of technology by considering various determinants that affect the intention and actual technology use behaviour of the users.

The study suggests four independent variables, namely, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) based on the initial UTAUT model and the empirical evidence in the existing studies that these variables should influence Behavioural Intention to Use AI. Performance expectancy indicates the views of students that AI technologies can enhance academic performance and learning outcomes. Effort Expectancy is a measure of the perceptions of students about the ease of learning and using AI technologies. Social Influence is the perceived support and demands of lecturers, peers and social environments, whereas facilitating conditions are the accessibility of institutional and technological assistance needed to facilitate the adoption of AI.

The hypothesised framework presupposes that the stronger behavioural intention to use AI will be observed among students when they believe that AI is useful, convenient, socially accepted, and supported by the institutional resources. The framework was created based on the modification of the original UTAUT constructs to fit the educational setting and the aim of the research of AI adoption among students of HEI.

Table 1.0 Summary of Hypotheses Developed to be Tested in This Study

Notation	Hypothesis
H1	There is a significant relationship between performance expectancy and behavioural intention to use.

H2	There is a significant relationship between effort expectancy and behavioural intention to use.
H3	There is a significant relationship between social influence and behavioural intention to use.
H4	There is a significant relationship between facilitating conditions and behavioural intention to use.

DISCUSSION

Theoretical Implications

This proposed study will be able to add to the body of literature concerning technology acceptance theory and educational technology in two primary manners.

First, this proposed study is going to explore the original UTAUT model developed by Venkatesh et al. (2003) and concentrate upon its four main components (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) instead of applying the extended version of UTAUT2 (Venkatesh et al., 2016) or some additional variables like AI Literacy. By utilizing the original UTAUT model when researching Generative AI it should allow researchers to assess whether the traditional variables of performance expectancy, effort expectancy, social influence, and facilitating conditions remain significant predictors of technology acceptance for autonomous and high-technology applications such as Generative AI. In prior studies there has been considerable variation in the factors that affect AI technology adoption (Foroughi et al., 2023; Tang et al., 2025; Yacob et al., 2025; Du & Lv, 2024). As such, this proposed study could establish a base theoretical framework from which to understand the relative significance of social influence and facilitating conditions versus the remaining three core constructs of UTAUT in relation to student usage of Generative AI.

Additionally, this proposed study will contribute to the application of UTAUT specifically within Malaysia's higher education system. Research has demonstrated that technology adoption behavior can vary significantly based upon the culture, institution, and environment (Zhao et al., 2025). Nevertheless, very little empirical evidence currently exists to support the application of technology acceptance theories related to generative AI with respect to Malaysia's public universities. The proposed study will investigate how students within Malaysia's public university system utilize generative AI and how they perceive their institutions' and social environments influence their acceptance and utilization of generative AI. By providing this localized contextualization this proposed study contributes to a larger body of literature exploring how established technology acceptance constructs operate across varying higher education environments and international settings.

Practical Implications

The proposed conceptual model has two potential action implications for the leadership, academic policymakers, and instructors at UiTM Shah Alam as well as other higher education institutions.

Firstly, the proposed research can be the foundation for developing Academic Integrity Policies and Use of AI Policies for HEIs. Specifically, by focusing on both Social Influence and Facilitating Conditions, this could lead to identifying areas where additional Institutional Guidance regarding the proper and safe usage of AI Tools in course work is needed. These policies can specifically outline what are acceptable AI-Assisted Learning Activities versus those which are considered Academic Misconduct or Plagiarism. Given that many Students find it difficult to differentiate Ethical AI Assistance from Plagiarism (Mohsin, 2025), the proposed conceptual model can facilitate the creation of University Wide Guidelines providing students and faculty with clearer boundaries regarding how to responsibly utilize AI in an academic setting.

Secondly, the proposed conceptual framework can serve as an implication for Higher Education Policy, Digital Transformation and AI Development Programs. By creating a conceptualization of the various Factors Influencing Students' Usage of AI, Policymakers will have a foundation for initiating programs to increase students' AI Literacy, Digital Competency and Responsible Practices of Using AI in Universities.

Such programs can include Structured AI Literacy Programs, Digital Competency Development Programs, Academic Integrity Programs, and Institutional Support Mechanisms. As universities continue to adapt to Technological Change, Developing Students' AI Preparedness can become significant in enabling Graduates to have relevant Digital Skills necessary for their future Employment (Dwivedi et al., 2023). Furthermore, such efforts at the National Level can contribute to Malaysia's goal of becoming a Digitally Advanced and AI-Ready Country.

CONCLUSION

The pervasive integration of GenAI into higher education has shifted the academic discourse from resisting technology to managing its effective, ethical, and responsible adoption. While the GenAI tools provide many benefits in regards to academic productivity and the ability to locate relevant information, there also exist many drawbacks related to academic honesty and an excessive reliance upon them. This research conceptualized a theoretical framework based on the foundational Unified Theory of Acceptance and Use of Technology (UTAUT) to explore undergraduate students' behavioral intentions toward adopting AI at Universiti Teknologi MARA (UiTM), Shah Alam.

Conceptualizing performance expectancy, effort expectancy, social influence, and facilitating conditions was successful in addressing critical empirical inconsistencies, contextual limitations, and theoretical ambiguities found within the existing literature. Rather than providing the final empirical data, this paper provided a solid, empirically-based foundation which posits how specific local institutional supports and social norms influencing Malaysian undergraduates' AI adoption behaviors are anticipated. Moreover, this paper demonstrated the theoretical necessity of contextualizing universal technology acceptance models to reflect nation-specific educational environments and institutional dynamics.

Finally, this study bridged the gap between abstract technology acceptance theories and concrete educational administrative practices. As such, it is anticipated that future empirical validations of this proposed model will allow administrators, faculty members, and policy makers at UiTM and other similar Malaysian public universities to utilize empirical knowledge gained through this process. Specifically, this proposed model is expected to aid in creating and disseminating explicit guidelines for AI usage; assist in refining assessment design formats; enhance UiTM's institutional support structure; and develop undergraduate curriculum elements which foster responsible AI literacy. Using these proposed avenues for future research, this conceptual study laid the groundwork for assisting higher education institutions to establish a balance among utilizing the capabilities of artificial intelligence while maintaining and ensuring academic rigor and student intellectual growth.

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