Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 153-174

JOURNAL OF INFORMATION SYSTEM AND TECHNOLOGY MANAGEMENT (JISTM)
www.gaexcellence.com/jistm

GENERATIVE AI ADOPTION FOR ACADEMIC LEARNING AMONG FOUNDATION STUDENTS IN MALAYSIA: AN APPLICATION OF UTAUT2

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Article Info:

Article history:
Received date: 15.07.2026
Revised date: 28.07.2026
Accepted date: 20.08.2026
Published date: 10.09.2026

Abstract:

Generative artificial intelligence (GenAI) is becoming more common in education, particularly as students use AI tools to support their learning and academic work. Despite this growing use, little research has focused on what influences GenAI use among foundation students in Malaysia. This study examines students' intention to use GenAI and their actual use of it for academic learning based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). A quantitative approach was used, with data collected from Malaysian foundation students through a structured questionnaire. The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results showed that performance expectancy, social influence,

Journal of Information System and Technology Management
JISTM
EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 153-174

To cite this document:

Noh, N. H. M., Bakar, N. S. A., Kenyang, A. A., Ahmad, A. A., & Ibrahim, N. (2026). Generative AI Adoption for Academic Learning Among Foundation Students in Malaysia: An Application of Utaut2. *Journal of Information System and Technology Management, 11* (44), 153-174.

DOI: 10.35631/JISTM.1144011

habit, and behavioural intention had significant effects, whereas effort expectancy, facilitating conditions, hedonic motivation, and price value did not significantly affect behavioural intention. Facilitating conditions and habit also had significant effects on actual use behaviour. Overall, the results indicate that foundation students are more likely to use GenAI when they see clear academic benefits, are influenced by their surrounding environment, and have developed regular usage habits. The study adds to existing GenAI research by providing evidence from Malaysian foundation students and applying UTAUT2 within a pre-university setting.

Keyword:

Behavioural Intention, Foundation Students, Generative Artificial Intelligence, Genai, Malaysia, Use Behaviour, UTAUT2

Introduction

Generative artificial intelligence (GenAI) is now being used more widely in education, especially through applications such as ChatGPT. These tools can generate different types of content, such as text, explanations, summaries, ideas, and images, based on users' prompts. Some of the commonly used GenAI applications are ChatGPT, Google Gemini, and Claude. Among students, GenAI can be used to explain difficult topics, develop ideas, summarise information, and assist with writing. At the same time, its use has raised concerns about over-reliance, originality, and academic integrity. Baidoo-Anu et al. (2024) reported that students saw ChatGPT as useful and accessible for academic purposes but also raised concerns about inappropriate use and dependence on the technology. This shows that students may consider the usefulness of GenAI when deciding whether to use it for their studies.

GenAI is becoming more visible in Malaysian education, including among students at the pre-university level. Mahmud and Raus (2025) found that Malaysian pre-university TESL students used ChatGPT for activities such as brainstorming, simplifying concepts, personalising learning, and paraphrasing. Lee (2025) similarly found that pre-university business students considered GenAI useful for learning, although they were also aware of its limitations and academic concerns. This indicates that exposure to GenAI can begin before students enter university. Its use can also be seen among Malaysian university students. Chieh and Wong (2025) examined students' experiences with ChatGPT and Google Gemini and reported their use for learning support and interaction. Generative AI is therefore familiar to many students in the Malaysian education setting, although its usefulness may vary according to their individual learning needs.

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JISTM
EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 153-174

The increasing use of AI in education has also received attention from the Malaysian government. In 2025, the Ministry of Higher Education organised AI Day to promote AI adoption in higher education and allocated RM50 million for AI development in the sector (Google, 2025). The government has also announced a programme offering free access to selected AI applications for Malaysians aged 18 to 30 who complete digital and AI learning modules (Zahiid, 2026). Such initiatives give students greater opportunities to access AI tools and develop related skills.

As students gain more exposure to GenAI, it becomes relevant to understand what encourages them to use these technologies. One framework that can be used for this purpose is the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al (2003). The framework considers performance expectancy, effort expectancy, social influence, and facilitating conditions. Venkatesh et al. (2012), later extended UTAUT into UTAUT2 by adding hedonic motivation, price value, and habit. Together, these factors provide a way to examine how students' perceptions, social surroundings, available resources, and previous experience may relate to their technology use.

UTAUT and UTAUT2 have already been used to study GenAI adoption. Within Malaysia, Baharuddin et al. (2024) examined ChatGPT acceptance among undergraduate students, while Baharin et al. (2025) studied GenAI adoption among TVET students using UTAUT. Mohadis et al. (2026) applied an extended UTAUT2 framework to ChatGPT among medical students, and Mohamed et al. (2026) examined ChatGPT use among students at a Malaysian public university with additional factors alongside UTAUT variables. Similar applications can also be found in studies outside Malaysia, suggesting that UTAUT-based approaches are increasingly being used to understand GenAI use among students.

However, the Malaysian evidence is still concentrated on university students and particular groups. Malaysian pre-university research has mainly looked at students' experiences, perceptions, and uses of GenAI rather than testing the full UTAUT2 framework. Zhao et al. (2025) included Malaysian students in a cross-country study with China using an extended UTAUT2 model and additional personal factors. Although this provides useful evidence, the cross-country design makes it different from examining the core UTAUT2 relationships specifically among Malaysian foundation students.

This leaves a more specific question about what drives GenAI use at the foundation level. Foundation students are in a transitional stage between secondary education and university, and some are already using GenAI for learning. Yet, there is still limited evidence on which factors influence their intention to use GenAI and whether that intention translates into actual use. Therefore, this study applies UTAUT2 to examine behavioural intention and actual use of GenAI for academic learning among Malaysian foundation students. By focusing on this group, the study adds evidence from a pre-university population that has received less attention in Malaysian GenAI adoption research.

Literature Review

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced by Venkatesh et al. (2003) by combining eight earlier technology-acceptance theories. It proposed

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EISSN: 0128-1666
Volume 11 Issue 44 (September 2026) PP. 153-174

four main factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Age, gender, experience, and voluntariness were also included as moderators.

UTAUT was mainly developed for organisational technology use. To make it more suitable for voluntary and consumer settings, Venkatesh et al. (2012) developed UTAUT2. The model retained the original four factors and added hedonic motivation (HM), price value (PV), and habit (HT). It also examined FC as a predictor of both behavioural intention and actual use, while removing voluntariness as technology use in consumer settings is generally voluntary.

UTAUT2 is relevant for studying GenAI adoption among students because students usually choose whether to use these tools for their learning. GenAI use may also depend on more than its usefulness and ease of use, including enjoyment, perceived value, and previous experience. Therefore, UTAUT2 offers a broader basis for understanding students' intention and actual use of GenAI.

Adoption of Generative AI (GenAI) Using UTAUT and UTAUT2

The rapid growth of GenAI, particularly since the introduction of ChatGPT, has led to increasing interest in technology-acceptance research. UTAUT and UTAUT2 have been widely used to examine students' intention and actual use of GenAI. However, findings differ across studies, suggesting that the influence of UTAUT2 factors may depend on the study context.

Strzelecki (2024) found that habit, performance expectancy, and hedonic motivation significantly influenced students' intention to use ChatGPT. Behavioural intention also strongly predicted actual use, while habit and facilitating conditions directly influenced use. Similarly, Habibi et al. (2023), found that facilitating conditions strongly predicted behavioural intention among Indonesian students, while effort expectancy was not significant. These findings indicate that different UTAUT2 factors may become more important across educational settings.

Other studies also show mixed results. Cabero-Almenara et al. (2024) found several UTAUT2 factors to be significant among university teachers. In contrast, Moradi (2025), found that habit, performance expectancy, and social influence influenced behavioural intention among Chinese EFL students, while effort expectancy, hedonic motivation, and price value were not significant. Facilitating conditions also predicted actual use but not behavioural intention. Ren et al. (2026) further reported that several factors, including performance expectancy, effort expectancy, hedonic motivation, price value, and habit, influenced GenAI adoption intention among Pakistani university students. Overall, these studies suggest that UTAUT2 provides a useful framework for understanding GenAI adoption, but its individual factors do not operate consistently across different populations and educational contexts.

Adoption of Generative AI Using UTAUT/ UTAUT2 in Malaysia

The Malaysian context is important because research on GenAI adoption using UTAUT and UTAUT2 is still limited. Zhao et al. (2025) examined students in Malaysia and China using an extended UTAUT2 model and found differences in the factors influencing GenAI adoption between the two groups. However, its cross-country design and use of additional factors mean that it did not directly test the core UTAUT2 model among Malaysian students. This leaves room for further research within a specific Malaysian student population.

Malaysian studies have nevertheless shown that UTAUT-related factors are relevant to GenAI adoption, although their effects differ across educational settings. Baharuddin et al. (2024) found several UTAUT factors to be associated with ChatGPT adoption among Malaysian undergraduates. Similarly, Baharin et al. (2025) found that performance expectancy and facilitating conditions influenced GenAI adoption among Malaysian TVET students. Importantly, the latter examined more than one GenAI tool, including ChatGPT and Gemini.

UTAUT2 research also shows that its additional factors may differ across student groups. Mohadis et al. (2026) found that habit and facilitating conditions were important for ChatGPT adoption among Malaysian medical students, while several other UTAUT2 factors were not significant. This differs from studies where performance expectancy and effort expectancy were significant, suggesting that the importance of these factors may depend on students' educational background and experience with GenAI. Mohamed et al. (2026) further found that UTAUT-related factors were relevant to ChatGPT adoption among students at a Malaysian public university, with behavioural intention also influencing actual use.

Hypothesis Development

Performance Expectancy and Behavioural Intention

Performance expectancy (PE) refers to the extent to which a person believes that using a technology can improve task performance (Venkatesh et al., 2012). In the context of generative artificial intelligence (GenAI), performance expectancy reflects students' perceptions that the technology can support their learning, improve productivity, and assist with academic tasks. When students see clear academic benefits, they are more likely to intend to use GenAI. Previous studies generally support the positive relationship between PE and behavioural intention (BI) in GenAI adoption. Strzelecki (2024) and Moradi (2025) found that PE significantly influenced students' intention to use ChatGPT. Similar findings were reported by Baharuddin et al. (2024) among Malaysian undergraduates and Baharin et al. (2025) among Malaysian TVET students. Therefore, the following hypothesis is proposed:

H1: Performance expectancy has a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Effort Expectancy and Behavioural Intention

Effort expectancy (EE) refers to the degree of ease associated with using a technology (Venkatesh et al., 2012). For GenAI, it reflects students' perceptions of how easily they can learn, understand, and use AI tools for academic purposes. When a technology is easy to use, users may face fewer difficulties when adopting it. Previous studies have reported mixed findings. Baharuddin et al. (2024) found that EE significantly influenced students' intention to use ChatGPT, while Cabero-Almenara et al. (2024) reported a positive effect on GenAI acceptance among university teachers. Since foundation students may have different levels of experience with GenAI, EE remains relevant to examine in this context. Therefore, the following hypothesis is proposed:

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H2: Effort expectancy has a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Social Influence and Behavioural

Social influence (SI) refers to the extent to which an individual perceives that important people believe he or she should use a particular technology (Venkatesh et al., 2012). n education, students may be influenced by lecturers, classmates, and friends. Thus, they may be more willing to use GenAI when its use is accepted or encouraged by people around them.

Previous studies generally support the relationship between SI and behavioural intention. Baharuddin et al. (2024), Moradi (2025) and Cabero-Almenara et al. (2024) reported positive relationships between SI and GenAI acceptance. However, the effect of SI may vary across different learning environments. For foundation students, interactions with peers and lecturers may make social influence more relevant to their willingness to use GenAI for learning. Therefore, the hypothesis is as follow:

H3: Social influence has a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Facilitating Conditions and Behavioural Intention

Facilitating conditions (FC) refer to the extent to which an individual believes that the organisational and technical resources necessary to use a technology are available (Venkatesh et al., 2012). In the context of GenAI-based learning, facilitating conditions may include access to appropriate devices, reliable internet connectivity, sufficient knowledge of AI tools, and the availability of technical or institutional support. Previous studies generally support the role of FC in GenAI adoption, although the findings are not always consistent. Habibi et al. (2023) identified FC as a strong predictor of ChatGPT adoption among Indonesian higher-education students. Malaysian studies by Baharuddin et al. (2024), Baharin (2025) and Mohadis et al. (2026) also reported significant relationships between FC and behavioural intention. These findings suggest that students are more likely to intend to use GenAI when they have the necessary resources and support. Therefore, the hypothesis is as follows:

H4: Facilitating conditions have a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Hedonic Motivation and Behavioural Intention

Hedonic motivation (HM) refers to the enjoyment, pleasure, or fun associated with using a technology (Venkatesh et al., 2012). Although GenAI is primarily adopted for functional purposes such as searching for information, explaining concepts, generating ideas, and supporting academic work, the interactive nature of conversational AI may also make its use enjoyable and engaging. Such positive experiences may encourage students to develop stronger intentions to use GenAI. Strzelecki (2024) found that hedonic motivation significantly influenced students' intention to use ChatGPT, while Cabero-Almenara et al. (2024) found that HM significantly influenced students' intention to use ChatGPT, while Cabero-Almenara et al. Thus, the following hypothesis is proposed:

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H5: Hedonic motivation has a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Price Value and Behavioural Intention

Price value (PV) refers to the consumer's cognitive trade-off between the perceived benefits of a technology and the monetary cost associated with using it (Venkatesh et al., 2012). Although many GenAI tools are free, some offer paid plans with additional features. Therefore, students may consider whether these added benefits are worth the cost. Ren et al. (2026) Although many GenAI tools are free, some offer paid plans with additional features. Therefore, students may consider whether these added benefits are worth the cost. Ren et al. Thus, the following hypothesis is proposed:

H6: Price value has a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Habit and Behavioural Intention

Habit (HT) refers to the extent to which individuals tend to perform a behaviour automatically as a result of prior learning and repeated experience (Venkatesh et al., 2012). In GenAI-based learning, repeated use of AI tools for activities such as obtaining information, understanding difficult concepts, generating ideas, summarising materials, or assisting with academic tasks may gradually transform GenAI use into a routine learning behaviour. Previous studies generally support the role of habit in shaping behavioural intention. Strzelecki (2024) identified habit as a strong predictor of students' intention to use ChatGPT, while Moradi (2025) reported a positive relationship among Chinese university EFL students. Malaysian evidence from Mohadis et al. (2026) also supports the influence of habit on students' intention to use ChatGPT. Thus, students who frequently use GenAI may be more likely to intend to continue using it for their academic learning. Accordingly, the following hypothesis is proposed:

H7: Habit has a significant positive effect on students' behavioural intention to use GenAI for academic learning.

Behavioural Intention and Use Behavioural

Behavioural intention represents an individual's willingness or intention to perform a particular behaviour. Within UTAUT2, behavioural intention is a proximal determinant of actual use behaviour because individuals who intend to use a technology are more likely to subsequently engage in that behaviour (Venkatesh et al., 2012). Previous studies generally support this relationship in GenAI adoption. Strzelecki (2024), (2023), Ren et al. (2026) and Mohamed et al. (2026) all reported a significant relationship between behavioural intention and actual GenAI use among students. This suggests that students with stronger intentions to use GenAI are more likely to use it in their academic activities. Thus, the following hypothesis is proposed:

H8: Behavioural intention has a significant positive effect on students' use behaviour of GenAI for academic learning.

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Facilitating and Use Behavioural

UTAUT2 proposes that facilitating conditions can influence not only behavioural intention but also actual use behaviour (Venkatesh et al., 2012). This distinction may be relevant because students can intend to use GenAI but still face practical difficulties when using it. Problems such as limited internet access, unsuitable devices, lack of technical knowledge, or insufficient support may affect their actual use. Strzelecki (2024) and Moradi (2025) also found that facilitating conditions significantly affected ChatGPT use behaviour. This may explain why facilitating conditions were significant for actual use in the present study, even though they did not affect behavioural intention. Students may already want to use GenAI, but having the necessary resources and support can make it easier for them to use it in their academic work. Thus, the following hypothesis is proposed:

H9: Facilitating conditions have a significant positive effect on students' use behaviour of GenAI for academic learning.

Habit and Use Behaviour

UTAUT2 proposes that habit can directly influence actual use behaviour (Venkatesh et al., 2012). Repeated use of GenAI for academic work may make it part of students’ normal study routines, making them more likely to use it regularly. Strzelecki (2024) and Mohadis et al. (2026) also reported a significant relationship between habit and actual GenAI use. Thus, the following hypothesis is proposed:

H10: Habit has a significant positive effect on students' use behaviour of GenAI for academic learning.

Methodology

Sampling

Participants were selected from the Foundation Programme at Universiti Malaysia Terengganu (UMT) students using convenience sampling. This method involves selecting participants who are easily accessible to the researcher (Bornstein et al., 2013). Convenience sampling was considered appropriate for this study as the intended students were readily accessible within the university, making the data collection process more feasible in terms of both time and resources.

The minimum sample size was determined using an a priori power analysis in G*Power 3.1 (Faul et al., 2009). Following Cohen’s (1988) guidelines, a medium effect size of 0.15 (f^2), a significance level of 0.05, and statistical power of 0.80 were specified. The model contained seven predictors for the endogenous construct with the highest number of predictors, resulting in a minimum requirement of 153 respondents. A total of 170 usable responses were obtained, exceeding the required sample size. A post hoc analysis indicated an achieved power of approximately 0.97, confirming that the sample was sufficient for the planned analysis.

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Data Collection

Data were collected through an online questionnaire created using Google Forms. The questionnaire used a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). It consisted of 32 items covering nine constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioural Intention, and Use Behaviour. The items measured students' perceptions, intentions, and actual use of GenAI for academic learning.

Measures and Instrument

A structured questionnaire was used to collect the data for this study. It contained 32 items across two sections. The first section collected respondents' background information, including gender, SPM background, previous experience with GenAI, familiarity with GenAI tools, and frequency of using GenAI for academic purposes. The second section measured the variables in the conceptual framework, namely Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioural Intention, and Use Behaviour.

Table 1 shows the constructs and their respective measurement items. The items were adapted from measures used in previous studies to suit the context of GenAI use for academic learning among Foundation Programme students. Some wording was adjusted to make the items clearer and more relevant to the respondents.

Table 1: Overview of the Constructs

Construct	Item
Performance Expectancy, PE	4
Effort Expectancy, EE	4
Social Influence, SI	3
Facilitating Conditions, FC	3
Hedonic Motivation, HM	3
Price Value, PV	3
Habit, HB	4
Behavioural Intention, BI	3
Use Behaviour, UB	4

Source: Adapted from Venkatesh et al. (2012).

Results

Respondents' Profile

Table 2 shows the demographic characteristics of the 170 students included in the final dataset. There were 93 female respondents (54.7%) and 77 male respondents (45.3%), with female students making up a slightly larger proportion of the sample. Most respondents were from the STEM A background, with 139 students (81.8%). KSI accounted for 12 students (7.1%), followed by STEM B with 10 students (5.9%) and STEM C with 9 students (5.3%). Thus, the sample was largely represented by STEM A students. For previous experience with GenAI tools, 120 students (70.6%) reported moderate experience. Another 30 students (17.6%) reported minimal experience, while 17 students (10.0%) reported extensive experience. Only

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3 students (1.8%) had no previous experience. This shows that most respondents had some experience with GenAI before taking part in the study. A similar pattern was found for familiarity with GenAI. Most students, 125 (73.5%), reported being moderately familiar with GenAI, while 37 (21.8%) were very familiar. Only 8 students (4.7%) reported no familiarity. For academic use, 92 students (54.1%) reported using GenAI seldom, while 78 (45.9%) reported always using it. No respondent selected the never category. Overall, the demographic findings show that the respondents generally had some level of previous experience and familiarity with GenAI tools, with moderate experience and familiarity being the most common responses. Nevertheless, academic usage was somewhat less frequent, as a slightly larger proportion of students reported using GenAI tools seldom rather than always.

Table 2: Demographic Information

Characteristics	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	77	45.3
	Female	93	54.7
SPM Background	KS1	12	7.1
	STEM A	139	81.8
	STEM B	10	5.9
	STEM C	9	5.3
Prior Experience with Gen AI Tools	Extensive Experience	17	10.0
	Moderate Experience	120	70.6
	Minimal Experiences	30	17.6
	No Experience	3	1.8
Familiarity with GenAI Tools	Very Familiar	37	21.8
	Moderately Familiar	125	73.5
	Not at All Familiar	8	4.7
Frequency of GenAI Usage for Academic Purposes	Always	78	45.9
	Seldom	92	54.1
	Never	0	0.0

Source: Authors

Partial Least Squares-Structural Equation Modelling

The proposed research model was evaluated using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 3.0 (Ringle et al., 2015). The analysis was conducted in two main stages. First, the measurement model was examined to establish the reliability and validity of the constructs. This was followed by an evaluation of the structural model to determine the relationships between the constructs and assess the proposed hypotheses, consistent with the two-step procedure recommended by Anderson and Gerbing (1988).

As the independent and dependent constructs were measured through a common self-administered questionnaire, the possibility of common method variance (CMV) was considered. Following the recommendation of Podsakoff et al. (2003), Harman's single-factor test was performed to assess whether a substantial amount of variance could be attributed to a single factor. The results showed that the first unrotated factor explained 49.23% of the total

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variance, which was below the commonly applied 50% criterion. Hence, the results did not indicate a substantial common method variance problem in the dataset.

The distributional characteristics of the data were subsequently examined using Mardia's measures of multivariate skewness and kurtosis, following the recommendations of Hair et al. (2021) and Cain et al. (2017). The analysis produced a Mardia's multivariate skewness coefficient of $\beta = 9.5966$ ($p < 0.01$), exceeding the suggested cut-off value of +1. The corresponding multivariate kurtosis coefficient was $\beta = 454.9036$ ($p < 0.01$), which was also substantially higher than the recommended cut-off of +20. These results indicate that the data did not satisfy the assumption of multivariate normality. Accordingly, PLS-SEM was considered an appropriate analytical technique for examining the proposed research model.

Measurement Model

The reflective measurement model was assessed to determine whether the indicators adequately represented their respective constructs in terms of reliability and validity as suggested by Hair et al., (2016). This assessment examined the quality of the measurement items and their ability to consistently measure the intended constructs. Outer loadings, composite reliability (CR), and average variance extracted (AVE) were examined to assess the convergent validity and reliability of the measurement model. The findings in Table 3 show that the outer loadings ranged from 0.734 to 0.912**,** with all indicators exceeding the recommended threshold of 0.708 (Hair et al., 2021). Therefore, all indicators demonstrated a sufficiently strong relationship with their respective constructs, indicating adequate convergent validity. The composite reliability (CR) and average variance extracted (AVE) were then examined to further assess the reliability and convergent validity of the constructs. Hair et al. (2021) recommended an AVE value of at least 0.50. As shown in Table 3, the CR values ranged from 0.898 to 0.942, exceeding the recommended threshold of 0.70. Similarly, the AVE values ranged from 0.638 to 0.803, exceeding the recommended value of 0.50. The results show that all constructs achieved acceptable internal consistency reliability and convergent validity. As shown in Table 3, the outer loadings, CR, and AVE values met the required criteria. The measurement model was therefore considered adequate for the structural model analysis.

Table 3: Reliability and Convergent Validity

Construct	Items	Outer Loadings	CR	AVE
Performance Expectancy (PE)	PE1	0.856	0.924	0.752
	PE2	0.874		
	PE3	0.849		
	PE4	0.888		
Effort Expectancy (EE)	EE1	0.772	0.905	0.705
	EE2	0.857		
	EE3	0.851		
	EE4	0.875		
Social Influence (SI)	SI1	0.914	0.952	0.870
	SI2	0.948		
	SI3	0.936		
Facilitating Conditions (FC)	FC1	0.923	0.915	0.781
	FC2	0.862		
	FC3	0.866		

Hedonic Motivation (HM)	HM1	0.957	0.971	0.918
	HM2	0.966		
	HM3	0.951		
Price Value (PV)	PV1	0.777	0.835	0.63
	PV2	0.712		
	PV3	0.884		
Habit (HB)	HB1	0.885	0.946	0.813
	HB2	0.900		
	HB3	0.934		
	HB4	0.887		
Behavioural Intention (BI)	BI1	0.906	0.945	0.85
	BI2	0.933		
	BI3	0.927		
Use Behaviour (UB)	UB1	0.911	0.935	0.782
	UB2	0.865		
	UB3	0.914		
	UB4	0.846		

Source: Authors

The HTMT ratio was used to assess discriminant validity, with values below 0.90 considered acceptable (Henseler et al., 2015). As shown in Table 4, all HTMT values were below this threshold. This indicates that the constructs were sufficiently distinct and that discriminant validity was achieved.

Table 4: Discriminant Validity

	PE	EE	SI	FC	HM	PV	HB	BI	UB
PE									
EE	0.567								
SI	0.767	0.518							
FC	0.708	0.821	0.602						
HM	0.668	0.578	0.612	0.546					
PV	0.747	0.652	0.797	0.811	0.632				
HB	0.646	0.4	0.65	0.532	0.635	0.61			
BI	0.728	0.436	0.745	0.559	0.645	0.689	0.788		
UB	0.734	0.516	0.7	0.659	0.628	0.718	0.877	0.842	

Source: Authors

Structural Model

After establishing the adequacy of the measurement model, the structural model was examined to assess the proposed relationships between the constructs. The analysis focused on the path coefficient (β), standard error (SE), t-value, p-value, confidence interval, and variance inflation factor (VIF). Hypothesis testing was conducted through PLS bootstrapping based on 5,000 resamples, in accordance with the recommendation of Hair et al. (2021).

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The results in Table 5 indicate that five out of the ten proposed relationships reached statistical significance, whereas the other five did not. The analysis showed that PE positively predicted BI ($\beta = 0.154$, $t = 2.063$, $p < 0.05$) , providing support for H1. On the other hand, the relationship between EE and BI was not statistically significant ($\beta = -0.052$, $t = 0.756$, $p > 0.05$); hence, H2 was not supported. SI was found to have a significant positive relationship with BI ($\beta = 0.255$, $t = 3.179$, $p = 0.001 < 0.05$), supporting H3. In contrast, FC did not significantly predict BI ($\beta = 0.028$, $t = 0.311$, $p > 0.05$), and therefore H4 was not supported. The results also showed that HM had no significant effect on BI ($\beta = 0.112$, $t = 1.585$, $p > 0.05$), while PV likewise failed to demonstrate a significant relationship with BI ($\beta = 0.052$, $t = 0.661$, $p > 0.05$). Consequently, both H5 and H6 were rejected. A significant positive relationship was observed between HB and BI ($\beta = 0.393$, $t = 5.101$, < 0.05) supporting H7. The findings further indicated that BI significantly predicted UB ($\beta = 0.320$, $t = 4.275$, < 0.05), providing support for H8. FC also demonstrated a significant positive effect on UB ($\beta = 0.190$, $t = 3.371$, < 0.05), supporting H9. The strongest relationship among the hypothesised paths was observed between HB and UB ($\beta = 0.484$, $t = 6.628$, < 0.05), supporting H10. Based on the magnitude of the significant path coefficients, HB → UB showed the largest effect ($\beta = 0.484$), followed by HB → BI ($\beta = 0.393$) and BI → UB ($\beta = 0.320$). Overall, the findings suggest that habitual use is particularly important in explaining both students' intention to use GenAI and their actual use behaviour. In addition, behavioural intention and the availability of facilitating conditions appear to play meaningful roles in explaining actual GenAI use.

The structural model was also examined for multicollinearity among the predictor constructs using VIF. According to Hair et al. (2021), VIF values below 5 indicate that collinearity does not represent a critical issue. Table 5 shows that the VIF values ranged between 1.954 and 2.901, which are all comfortably below the recommended threshold. Thus, the structural model does not appear to suffer from problematic multicollinearity, and the predictor constructs can be considered sufficiently independent for the subsequent interpretation of the structural relationships.

Table 5: Path Coefficient and Hypothesis Testing

	Beta	SE	T Values	P Values	LL	UL	VIF	Decision
PE → BI	0.154	0.077	2.063	0.039	0.002	0.306	2.623	Supported
EE → BI	-0.052	0.069	0.756	0.45	-0.188	0.086	2.274	Not Supported
SI → BI	0.255	0.081	3.179	0.001	0.092	0.409	2.509	Supported
FC → BI	0.028	0.083	0.311	0.756	-0.137	0.194	2.901	Not Supported
HM → BI	0.112	0.071	1.585	0.113	-0.03	0.249	2.113	Not Supported
PV → BI	0.052	0.076	0.661	0.509	-0.094	0.203	2.3	Not Supported
HB → BI	0.393	0.077	5.101	0	0.244	0.543	1.954	Supported
BI → UB	0.320	0.075	4.275	0	0.177	0.467	2.265	Supported

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FC → UB	0.190	0.056	3.371	0.001	0.081	0.303	1.391	Supported
HB -→UB	0.484	0.073	6.628	0	0.339	0.625	2.19	Supported

Source: Authors

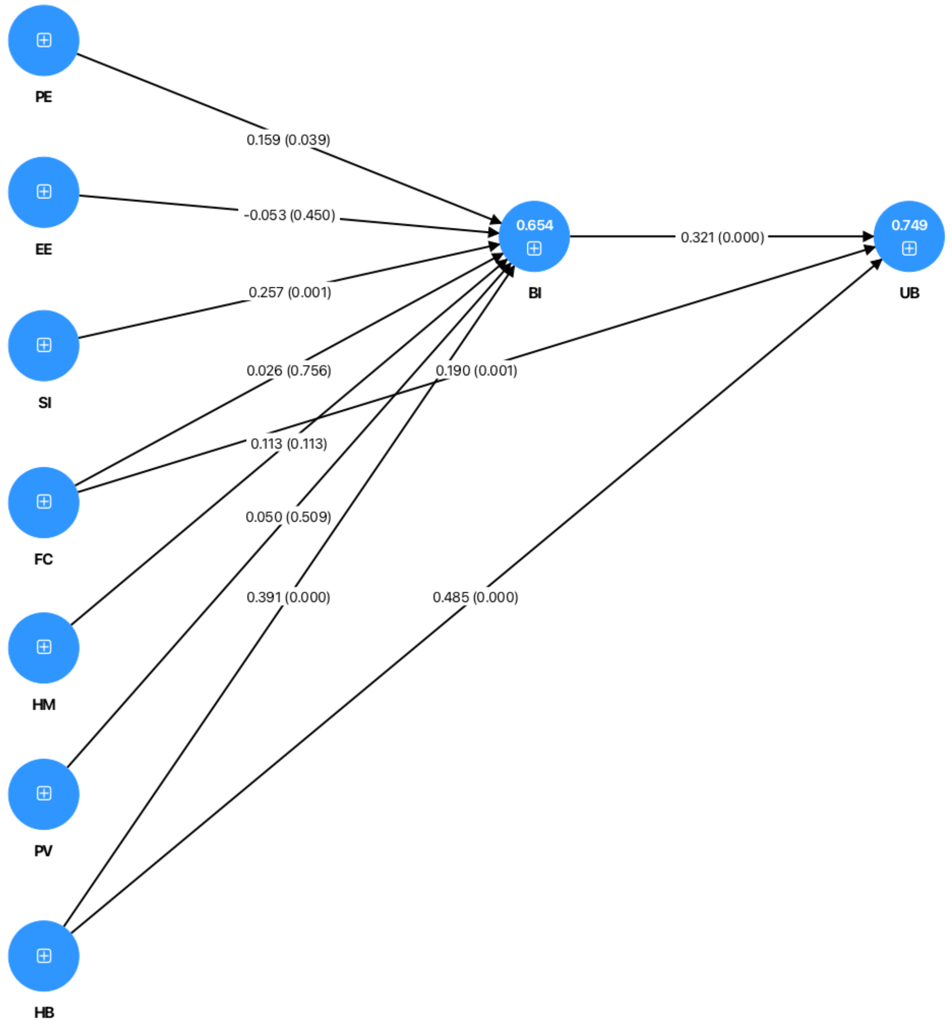

Figure 1: Structural Model

Source: Authors

The predictive capability of the structural model was first examined through the coefficient of determination (R^2). This value indicates the proportion of variance in an endogenous construct that can be accounted for by its corresponding predictor constructs. Based on Chin, (1998), R^2 values of 0.19, 0.33, and 0.67 represent weak, moderate, and substantial explanatory power, respectively. As shown in Table 6, BI recorded an R^2 of 0.654, indicating that the predictors explained 65.4% of its variance and represented moderate explanatory power. Meanwhile, UB recorded an R^2 of 0.749, indicating substantial explanatory power, with 74.9% of its variance explained by the model.

The effect size (f^2) was examined to determine the extent to which each exogenous construct contributed to its respective endogenous construct. Following Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 can be interpreted as representing small, medium, and large effects, respectively.

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For BI, HB showed the largest effect (f^2 = 0.226), followed by SI (f^2 = 0.076) and PE (f^2 = 0.028), while EE, FC, HM, and PV produced effects below the small-effect level. For UB, HB demonstrated a large effect (f^2 = 0.427), whereas BI showed a medium effect (f^2 = 0.181) and FC showed a small effect (f^2 = 0.103). These findings indicate that habit made the greatest contribution to explaining both behavioural intention and actual GenAI use behaviour.

Moreover, the predictive relevance of the structural model was evaluated using the Q^2 statistic. Hair et al. (2021), suggest that a Q^2 value greater than zero indicates that the model has predictive relevance for the corresponding endogenous construct. As reported in Table 6, the Q^2 values were 0.615 for BI and 0.542 for UB, with both values exceeding zero. Hence, the structural model demonstrated predictive relevance for both behavioural intention and use behaviour, further indicating its satisfactory predictive capability.

Table 6: R2 and Effect Size

	R^2	Q^2	f^2	
			BI	UB
PE			0.028	
EE			0.004	
SI			0.076	
FC			0.001	0.103
HM			0.017	
PV			0.003	
HB			0.226	0.427
BI	0.654	0.615		0.181
UB	0.749	0.542		

Source: Authors

Discussion

This study examined the factors influencing foundation students' behavioural intention and actual use of generative artificial intelligence (GenAI) for academic learning using the UTAUT2 framework. Specifically, the study examined PE, EE, SI, FC, HM, PV and HB as predictors of BI, while also examining BI, FC, and HB as predictors of UB. The findings provide mixed evidence, suggesting that foundation students' adoption of GenAI is influenced more strongly by its academic value, social environment, and established usage patterns than by ease of use, enjoyment, cost, or access when forming their intention to use the technology.

The findings support H1, indicating that performance expectancy has a significant positive effect on students' behavioural intention to use GenAI for academic learning. This finding is aligned with and supports the findings of Strzelecki (2024), Moradi (2025), Baharuddin et al. (2024), and Baharin et al. (2025). However, the result differs from Mohadis et al. (2026), who reported an insignificant relationship between performance expectancy and behavioural intention. The significant relationship may be attributed to foundation students' emphasis on the practical academic benefits of GenAI. Lee (2025), based on focus-group discussions with Malaysian pre-university students, found that GenAI supported learning through personalised and accessible assistance. Similarly, Mahmud and Raus (2025) reported that Malaysian pre-university students used ChatGPT to generate ideas, clarify complex concepts, personalise learning, and improve their writing. Thus, foundation students may be more willing to use GenAI when they can directly see its value in addressing academic demands and supporting their transition into higher education.

In contrast, the findings do not support H2, as effort expectancy was found to have no significant effect on students' behavioural intention to use GenAI. This finding is consistent with Moradi (2025) and Mohadis et al. (2026), who also found no significant relationship between effort expectancy and behavioural intention. However, the finding contradicts Baharuddin et al. (2024), who reported a significant relationship. The non-significant finding may be because GenAI is already relatively easy and familiar to students. Klar et al. (2025) found that students generally perceived ChatGPT as easy to use because of its intuitive, chat-based interface. Similarly, a qualitative study by Lee (2025) involving Malaysian pre-university students showed that students were already using ChatGPT and other GenAI tools in their learning. Therefore, ease of use may have become less important in shaping foundation students’ intention, while the academic benefits provided by GenAI may carry greater importance.

Furthermore, the findings support H3, demonstrating that social influence has a significant positive effect on students' behavioural intention to use GenAI. This finding is aligned with and supports the findings of Baharuddin et al. (2024), Moradi (2025), and Cabero-Almenara et al. (2024). Therefore, the present finding provides further support for the role of social influence in GenAI adoption. The significant relationship may be explained by the strong role of peers and the learning environment in shaping foundation students’ use of GenAI. Mahmud and Raus (2025) found that Malaysian pre-university students discussed and used ChatGPT in their learning, particularly for brainstorming, simplifying ideas, and other academic tasks. Similarly, Lee (2025) found that GenAI use had become part of students’ learning experiences in a Malaysian pre-university setting. Therefore, foundation students may be more willing to use GenAI when its use is familiar and accepted among their classmates and within their learning environment.

However, the findings do not support H4, as facilitating conditions were found to have no significant effect on students' behavioural intention to use GenAI. This finding contradicts the findings of Baharuddin et al. (2024), Baharin et al. (2025), and Mohadis et al. (2026), who reported significant relationships between facilitating conditions and behavioural intention. However, the finding is consistent with Strzelecki (2024), who also found that facilitating conditions did not significantly influence behavioural intention. The non-significant relationship may be because GenAI is already relatively accessible to foundation students through commonly available devices and online platforms. This is consistent with Lee (2025), who found that Malaysian pre-university students were already using GenAI as part of their learning. Similarly, Chieh and Wong (2025) found that Malaysian university students viewed ChatGPT and Gemini as accessible learning tools. Therefore, facilitating conditions may be less important in forming students’ initial intention to use GenAI, but more important in enabling them to use the technology in practice, as reflected in H9.

Similarly, the findings do not support H5, as hedonic motivation was found to have no significant effect on students' behavioural intention to use GenAI. This finding is consistent with Moradi (2025) and Mohadis et al. (2026). However, it differs from and does not support the findings of Strzelecki (2024) and Cabero-Almenara et al. (2024), who reported significant effects of hedonic motivation. The non-significant finding may be because foundation students mainly use GenAI to support their academic work rather than for enjoyment. Mahmud and Raus (2025), in a qualitative study of Malaysian pre-university students, found that students used ChatGPT mainly for learning and writing-related tasks. Similarly, Baidoo-Anu et al. (2024) found that students primarily valued ChatGPT for academic benefits such as understanding difficult topics and completing assignments. Thus, enjoyment may be less important to foundation students than the practical academic benefits obtained from GenAI.

Likewise, the findings do not support H6, indicating that price value has no significant effect on students' behavioural intention to use GenAI. This finding is consistent with Moradi (2025) but contradicts the findings of Ren et al. (2026), who reported a significant relationship between price value and GenAI adoption intention. The non-significant finding may be because foundation students can access basic GenAI services without paying. Foung et al. (2024) noted that students distinguished between the features available in free and premium versions, suggesting that paid features may be viewed as additional rather than essential. Similarly, Baidoo-Anu et al. (2024) found that students generally regarded ChatGPT as accessible and used it mainly for academic tasks. Therefore, price may have limited influence on foundation students' intention when free options already provide sufficient support for their learning needs.

In addition, the findings support H7, demonstrating that habit has a significant positive effect on students' behavioural intention to use GenAI. This finding is strongly aligned with and supports the findings of Strzelecki (2024), Moradi (2025), and Mohadis et al. (2026). The significant relationship may be because repeated use has made GenAI part of foundation students' normal study routines. Mahmud and Raus (2025) found that Malaysian pre-university students regularly used ChatGPT for tasks such as brainstorming, simplifying concepts, and supporting writing. Similarly, Lee (2025) reported that GenAI had become part of the learning experiences of Malaysian pre-university students. Thus, frequent exposure to GenAI may make its use more familiar and routine, increasing students' intention to continue using it.

The findings support H8, demonstrating that behavioural intention has a significant positive effect on students' actual use behaviour of GenAI. This finding is consistent with and strongly supports previous findings reported by Strzelecki (2024), Habibi et al. (2023), Ren et al. (2026), and Mohamed et al. (2026). The significant relationship may be because students who already plan to use GenAI are more likely to incorporate it into their regular academic activities. Lee (2025) found that Malaysian pre-university students were already using GenAI for learning-related purposes, while Mahmud and Raus (2025) reported regular use of ChatGPT for tasks such as brainstorming, simplifying concepts, and writing support among Malaysian pre-university students. Thus, when foundation students have a clear intention to use GenAI, they may be more likely to turn that intention into actual use during their studies.

Interestingly, the findings support H9, demonstrating that facilitating conditions significantly influence students' actual use of GenAI. This finding is aligned with Strzelecki (2024) and Moradi (2025). This result also provides an important contrast with H4, where facilitating conditions did not significantly influence behavioural intention. This suggests that facilitating conditions may be more important when students actually use GenAI rather than when they decide whether they intend to use it. For foundation students, access to suitable devices, internet connectivity, and the necessary knowledge may not determine their initial intention because GenAI is already relatively accessible. However, these conditions become important when students need to use GenAI for actual academic tasks. This interpretation is consistent with

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Volume 11 Issue 44 (September 2026) PP. 153-174

Chieh and Wong (2025), who found that Malaysian university students experienced ChatGPT and Gemini as accessible tools for learning support.

Finally, the findings support H10, indicating that habit has a significant positive effect on students' actual use behaviour of GenAI. This finding is consistent with and supports the findings of Strzelecki (2024) and Moradi (2025), who similarly demonstrated the importance of habit in explaining actual GenAI use. The significant relationship may be because repeated use of GenAI can gradually become part of foundation students' normal study routines. Mahmud and Raus (2025) found that Malaysian pre-university students used ChatGPT for activities such as brainstorming, simplifying concepts, and writing support. Lee (2025) similarly reported that GenAI had become part of Malaysian pre-university students' learning experiences. Thus, as students become more accustomed to using GenAI for their studies, its use may become more routine and lead to more frequent actual use.

Overall, the findings indicate that GenAI adoption among foundation students is driven mainly by its perceived academic value, social environment, and established usage patterns. Performance expectancy, social influence, and habit were important in shaping behavioural intention, while behavioural intention, facilitating conditions, and habit were important in explaining actual use behaviour. In contrast, effort expectancy, facilitating conditions, hedonic motivation, and price value did not significantly influence behavioural intention. The difference between the intention and actual-use findings for facilitating conditions is particularly noteworthy, suggesting that having the intention to use GenAI and being able to use it in practice may involve different considerations. Taken together, the findings suggest that foundation students may adopt GenAI primarily because it is useful for their studies and has become increasingly familiar within their learning environment, while practical conditions and established habits become more important in sustaining actual use.

Conclusion

This study examined the factors related to foundation students' intention and actual use of GenAI for academic learning using UTAUT2. The results showed that performance expectancy, social influence, and habit were significant predictors of behavioural intention. Behavioural intention, facilitating conditions, and habit also had significant effects on actual use. However, effort expectancy, facilitating conditions, hedonic motivation, and price value were not significant predictors of behavioural intention. Habit had the strongest relationship with actual use (H10, $\beta = 0.484$), followed by its effect on behavioural intention (H7, $\beta = 0.393$). This suggests that students who regularly use GenAI are more likely to continue using it for their academic work. The results generally show that foundation students place greater importance on the practical value of GenAI, their surrounding social environment, and previous usage experience than on enjoyment, ease of use, or cost. The study also adds evidence to the relatively limited research on GenAI adoption among Malaysian foundation students and shows that the factors related to students' intention are not necessarily the same as those related to their actual use.

Recommendation

Based on the findings, several recommendations can be made for foundation students, educators, and educational institutions. First, educators should highlight the practical academic benefits of GenAI. Since performance expectancy significantly influenced behavioural

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intention, lecturers can introduce suitable GenAI tools for activities such as explaining difficult concepts, generating ideas, improving writing, and supporting learning. This can help students understand how GenAI can be used meaningfully in their studies. Second, students should be given more opportunities to use GenAI with proper guidance. The significant effect of social influence suggests that lecturers and peers can play a role in encouraging appropriate use. Workshops, classroom activities, and clear guidance on responsible use may help students develop better practices when using GenAI. Third, institutions should provide the necessary support for actual GenAI use. Although facilitating conditions did not affect behavioural intention, they had a significant effect on actual use. Reliable internet access, suitable devices, access to relevant GenAI tools, and basic user guidance can therefore help students use these technologies more effectively. Fourth, students should develop useful and responsible GenAI habits. Habit was the strongest predictor of both behavioural intention and actual use. However, regular use should be accompanied by appropriate guidance to ensure that GenAI supports students' learning rather than replacing their own effort and thinking. Finally, future research could examine other groups of Malaysian students and include additional factors that may explain GenAI adoption. Comparisons between foundation and undergraduate students, as well as across different disciplines and institutions, could provide a broader understanding of how GenAI use develops in Malaysian education.

Acknowledgements:	The authors would like to offer their profound gratitude to Universiti Teknologi MARA and Universiti Malaysia Terengganu, which has provided the requisite resources and support during the course of this research. The contribution of colleagues and peers who shared their valuable inputand positive feedback is highly appreciated, and it improved the quality of this paper to a great extent.
Funding Statement:	No Funding.
Conflict of Interest Statement:	This study was conducted in accordance with ethical research standards. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Ethics Statement:	This study was conducted in accordance with ethical research standards. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Author Contribution Statement:	All authors contributed significantly to the development of this manuscript. Nur Hidayah Md Noh and Agnes Ayang Kenyang was responsible for the conceptualization, methodology, and overall supervision of the study. Nurul Syahida Abu Bakar handled data collection, analysis, and interpretation of results. [Author C] contributed to the literature review, drafting, and critical revision of the manuscript. All authors read and approved the final version of the manuscript prior to submission.

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