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Perceived Intelligence and Perceived Anthropomorphism as Additional Predictors of ChatGPT Usage Behaviour

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ABSTRACT

The rapid advancement of generative artificial intelligence (AI) tools like ChatGPT is transforming various sectors, including education. Although many are adopting ChatGPT for learning, not all students are embracing it. This is because there are contrasting views regarding its usefulness, ease of use, reliability, and ethical implications. ChatGPT acceptance and usage behaviour have been frequently studied through the Unified Theory of Acceptance and Use of Technology (UTAUT) model. However, it may not completely describe the features of AI. Hence, this paper extends the UTAUT model by incorporating two constructs specifically on AI, namely, Perceived Intelligence and Perceived Anthropomorphism as predictors of the ChatGPT usage behaviour. The study followed a quantitative research design. Purposive sampling was used to collect data from 384 students at a public university in Northern Malaysia. Data was analyzed through Partial Least Squares Structural Equation Modeling. The results showed that all six predictors have significant effects on the Behavioural Intention with 48.3% of variance. Behavioural Intention predicts the actual Use Behaviour with 16.5% of variance. The results highlight the robustness of the extended UTAUT model, where the two constructs become predictors of behavioural intention to use. This indicated students' dependency on the perceived reasoning of ChatGPT. Based on these predictors, the study has constructed a behavioural model to determine the ChatGPT usage among university students. The findings contribute by demonstrating the validity of the extended UTAUT model. Additionally, practical recommendations are provided to universities, educators, and AI developers for integrating ChatGPT in academic settings.

Keywords: ChatGPT, generative artificial intelligence, perceived anthropomorphism, perceived intelligence, Unified Theory of Acceptance and Use of Technology (UTAUT).

INTRODUCTION

Recently, artificial intelligence (AI) has made its presence known in decision-making, communicating, and information systems in almost every field, including higher education (Hussein et al., 2025). One of the leading developments in this area is generative AI, which enables systems to create human-like text, explanations, and assist in complex cognitive tasks (Fui-Hoon Nah et al., 2023). ChatGPT is a conversational AI system developed by OpenAI that employs large-scale natural language processing and deep learning algorithms to generate human-like conversation (Hadi et al., 2023). It has become a valuable asset in individual learning and academic aid because of its impressive capabilities (Polyportis & Pahos, 2025). In higher education, ChatGPT is used frequently for tasks like summarising texts, drafting assignments, providing concept explanations, and offering individualized academic support. Implementing these functions improves learning effort and performance, enabling ChatGPT to enlarge learning spaces to offer students tremendous value from its usage (García-L Gómez et al., 2025). Nonetheless, ChatGPT has been facing a handful of acceptance difficulties. One of these difficulties includes ethical concerns like plagiarism and fake data. Additionally, issues on technological barriers like inadequate infrastructure, trust in its efficacy, and the difference between users' behavioural intention and actual usage, which is caused by unfamiliarity, also arise (Al-Afnan et al., 2023). All these issues need to be addressed before ChatGPT can be successfully implemented in educational settings (Murad et al., 2023).

Conventional technology acceptance models have been applied widely to examine individuals' acceptance of digital tools. Some of these models include the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behaviour (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). UTAUT investigates performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), which influence behavioural intention (BI) and use behaviour (UB). It had been noted that this model shows strong potential to predict the acceptance of e-learning, mobile banking, and more recently, generative AI, with both conventional and extended constructs (Polyportis & Pahos, 2025; Lal et al., 2024; Saxena et al., 2023). Yet, generative AI is different from prior technology in the possible way of human-like reasoning and interaction during conversation, which are beyond the conventional acceptance constructs (Mai & Khairani, 2026; Park et al., 2022; Long & Magerko, 2020; Islam, 2011).

When interacting with ChatGPT, users evaluate the system not only through its functional utility, but also through its emotional resonance and the degree of intelligence it exhibits in mimicking human thought. Given these distinct psychological dimensions, there is a clear need for an acceptance model tailored to these unique characteristics. To address this gap and offer a more comprehensive explanation of ChatGPT adoption, this study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating two additional constructs: Perceived Intelligence (PI) and Perceived Anthropomorphism (PA). Specifically, PI captures the user’s assessment of the AI's cognitive capabilities and intelligence (Collins et al., 2021; Madsen & Gregor, 2000), while PA reflects the extent to which the user perceives ChatGPT’s communication and interaction patterns as fundamentally human-like (Balakrishnan & Dwivedi, 2024; Epley et al., 2007).

AI systems have characteristics that are not well accounted for the conventional acceptance constructs, in particular the perceived intelligence and perceived anthropomorphism (Wang et al., 2023). Other than that, UTAUT does not encompass the cognitive and emotional aspects of AI, particularly for educational settings (Ko & Chang, 2023). Hence, by integrating the PI and PA into the UTAUT model, a deeper understanding of students' tendencies toward ChatGPT adoption could be gained. This structural combination mirrors recent hybrid modelling movements in educational technology research, where baseline technology acceptance constructs are integrated with post-acceptance variables or psychological motivation characteristics to better explain the factors driving students' behaviour (Mai & Khairani, 2026; Soliman et al., 2025). This is why the concept of PI indicates users' belief that ChatGPT can solve problems and improve in terms of learning, while PA reflects the extent of connection formed between a person and the technology through human interaction (Chinmulgund et al., 2023). These constructs shed light on the broader cognitive and emotional aspects that influence behavioural intention and use of ChatGPT (Venkatesh et al., 2003). Additionally, while ChatGPT has garnered significant global attention, empirical research predicting student adoption remains limited, particularly within the context of Asian and Malaysian higher education institutions (Budhathoki et al., 2024; Namatovu & Kyambade, 2025; Owan et al., 2025; Strzelecki, 2023). To address this literature gap, this study investigates three central research questions: first, how the core UTAUT constructs (Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)) impact higher education students' behavioral intention to use ChatGPT; second, whether psychology-based AI constructs, the PI and PA, influence this behavioral intention; and third, whether behavioral intention successfully predicts the actual use behavior of ChatGPT among these students.

The aim of this study is to fill the current theoretical and empirical gaps by extending the UTAUT model to accommodate generative AI–specific constructs, namely perceived intelligence and perceived anthropomorphism. The proposed hypotheses deepen the understanding of the technology acceptance of ChatGPT by emphasizing the importance of users' cognitive and emotional perception in ChatGPT adoption. With this study, empirical evidence is provided for the Malaysian higher education context. The content of the article is structured as follows: firstly, a review of previous works is provided. This is followed by the methodology, results, and discussion. The article ends with the conclusion of the study.

TECHNOLOGY ACCEPTANCE MODEL AND RELATED EMPIRICAL STUDIES

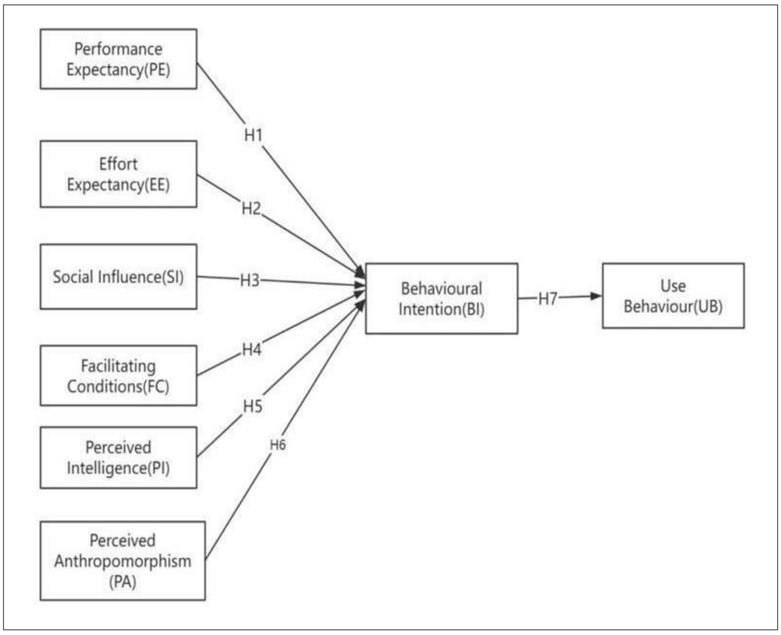
Earliest models that investigated the way individuals accept new technology include the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Reasoned Action (Fishbein & Ajzen, 1975), and the Theory of Planned Behaviour (Ajzen, 1991). TAM is aimed at perceived usefulness and ease of use. The Unified Theory of Acceptance and Use of Technology (UTAUT), on the other hand, encapsulates eight major models and is regarded as one of the more thorough models in explaining technology acceptance (Venkatesh et al., 2012; Venkatesh et al., 2003). UTAUT suggested the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioural intention and use behaviour. It may be very convincing and operates well on traditional digitized systems. However, it may not be sufficient to explain the adoption of a technology that simulates human cognition, which is considered a form of intelligence (Dwivedi et al., 2023). AI literacy is not just about understanding the use of smart technologies. Nevertheless, it involves more than that to form a critical, ethical, and practical understanding regarding the function of AI and its impact on human life (Long & Magerko, 2020).

Current empirical research has analyzed the adoption of ChatGPT in higher education settings using established models of technology acceptance, such as the UTAUT model. Previous findings highlight the predictive power of performance expectancy in students' behavioural intention to adopt ChatGPT. This implies that many learners are motivated to use technological tools that can enhance their learning efficiency and improve academic outcomes (Siddiqui et al., 2025; Budhathoki et al., 2024). In contrast, social influence exhibits varying impacts, which indicates that scholars are encouraged to adopt ChatGPT with self-centred effort rather than the pressure of peers and institutions (Siddiqui et al., 2025). Many studies have enhanced the original UTAUT model by adding more constructs or adopting UTAUT2 to address actual usage behaviours. For instance, constructs such as learning value, habit, anxiety, and hedonic motivation were examined in different contexts and cultural variations in countries like the UK, Nepal, Africa, Uganda, and Poland (Owan et al., 2025; Namatovu & Kyambade, 2025; Budhathoki et al., 2024; Strzelecki, 2024). These studies add value to the contextual constructs related to adoption and their usefulness. However, the strength of these extensions varies across contexts. Furthermore, limited studies have addressed the constructs that focus on AI, namely the cognitive and emotional perceptions of ChatGPT in the learning environment. Therefore, there is a clear necessity to extend the UTAUT model with the constructs that influence the cognitive and emotional factors on the acceptance of ChatGPT. With these constructs, learners' adoption of generative AI tools can be examined more accurately, since ChatGPT is different from conventional technologies.

The research model of this study is developed based on the UTAUT model to explore ChatGPT usage among higher education students. It is found that PE, EE, SI, FC, PI, PA, and BI are the predictors that can impact ChatGPT acceptance in higher education settings. PI and PA are two potential predictors introduced, which further enhance the UTAUT model. The intention is to present a more comprehensive model for evaluating ChatGPT acceptance in higher education settings. Therefore, the proposed model can be considered as follows: BI to be influenced by PE, EE, SI, FC, PI, and PA. This research model is shown in Figure 1.

Figure 1

Research Model



Performance Expectancy and ChatGPT Behavioural Intention

The Performance Expectancy (PE) represents the level of individuals' expectancy that the usage of a specific technology would result in improved performance or outcomes (Venkatesh et al., 2003). Previous studies have shown evidence that PE is one of the most influential predictors of user adoption of digital-learning tools or AI systems (Polyportis & Pahos, 2025; Siddiqui et al., 2025; Namatovu & Kyambade, 2025; Strzelecki, 2024; Gansser & Reich, 2021). In related studies, it has been observed that chatbot systems such as ChatGPT provide support to academic tasks when completing the assignment, especially in terms of improving conceptual comprehension and speeding up the learning process. Thus, the learners' intention to adopt is expected to increase when they expect that the use of ChatGPT can bring them improvements in their performance. Hence, in this study, PE refers to whether the higher education students perceive that the usage of ChatGPT could enable them to enhance their performance. Based on the aforementioned literature, this study formulates the following hypothesis:

H_1: There is a positive and significant relationship between performance expectancy and behavioural intention to use ChatGPT among higher education students.

Effort Expectancy and ChatGPT Behavioural Intention

Effort Expectancy (EE) relates to how easily a technology is used (Venkatesh et al., 2003). Earlier studies indicate that ease of use is one of the key predictors of the intent for users to use educational technology (Budhathoki et al., 2024; Strzelecki, 2024; Gansser & Reich, 2021). In relation to this, ChatGPT is an effective tool of natural language communication that simplifies interactions without technical knowledge or training. Having an easy conversational interface, this tool provides better support for its users (Hariri, 2023). Additionally, it supports the hypothesis that EE has a positive influence on usage intention. However, there exist studies that found contradictory results (Owan et al., 2025; Shittu & Taiwo, 2023). It might be caused by the influence of culture or the infrastructure. Herein, EE is defined to be the extent to which higher education students tend to perceive ChatGPT as easily used. Based on the aforementioned literature, this study formulates the following hypothesis:

H_2: There is a positive and significant relationship between effort expectancy and behavioural intention to use ChatGPT among higher education students.

Social Influence and ChatGPT Behavioural Intention

Social Influence (SI) means the extent to which individuals perceive that people who are important to them think they should use the new technology (Venkatesh et al., 2003). Students are likely to adopt new tools if influenced by lecturers or perceive that large portions of their social groups are using the tools. Past studies indicate that the role of SI in influencing the adoption of technology is essential, since SI from important individuals has positive impacts on users' behaviour (Namatovu & Kyambade, 2025; Owan et al., 2025; Budhathoki et al., 2024; Gansser & Reich, 2021). Moreover, since ChatGPT is widely covered across both social and academic forums and networks, SI may impact the adoption within the student population. Hence, herein, the role of SI is defined as the extent to which higher education students perceive their lecturers and the university provide support to use ChatGPT. Thus, the following hypothesis is proposed.

H_3: There is a positive and significant relationship between social influence and behavioural intention to use ChatGPT among higher education students.

Facilitating Conditions (FC) and ChatGPT Behavioural Intention

Facilitating conditions (FC) is defined as the extent to which individuals perceive that the necessary resources and sufficient support are available for them to use a particular technology effectively (Venkatesh et al., 2003). There are several studies that show FC can impact behavioural intention (Polyportis & Pahos, 2025; Budhathoki et al., 2024; Strzelecki, 2024). These studies show the contribution of the FC on technology adoption, although there is limited empirical evidence that are used for the educational settings (Polyportis & Pahos, 2025; Salloum et al., 2019). Meanwhile, there are factors that influence higher adoption of this technology within the universities' settings. Among them are the levels of AI literacy, a digital-friendly environment, and the institution supports. Since ChatGPT needs a secure internet connection, suitable devices and user support, FC plays an important role in students' acceptance of the tool (Namatovu & Kyambade, 2025). Herein, FC is used in this study to mean higher education students’ access to ChatGPT, the level of institutional acceptance, the frequency to which it can be used and the availability of training and technical assistance that can assist students using the tool most effectively. If all these conditions are available, the students might be willing to use the ChatGPT for academic-related purposes. Therefore, the following hypothesis is proposed.

H_4: There is a positive and significant relationship between facilitating conditions and behavioural intention to use ChatGPT among higher education students.

Perceived Intelligence (PI) and ChatGPT Behavioural Intention

User’s perception of the system’s intellectual and functional ability can be referred to as Perceived Intelligence (PI) on a system. Balakrishnan and Dwivedi (2024) concluded that in the voice assistant setting, the university’s impression about the intelligence could help to a positive user attitude. Nevertheless, there are limited studies about ChatGPT, specifically in the university environment. Based on the previous literature, a greater capability of information systems influences user attitudes (Rezvani et al., 2017). Additionally, for example, Duan et al. (2019) argue that intelligent architecture utilized in AI interfaces can lead to higher user acceptance because the system is more user-friendly and responsive to the users’ needs. The same idea was similarly reiterated by Collins et al. (2021), who proposed that intelligent architecture in the design of AI systems can help in achieving a richer and more productive user acceptance and positive attitudes. On the basis of the aforementioned literature, this study formulates the following hypothesis:

H_5: There is a positive and significant relationship between perceived intelligence and behavioural intention to use ChatGPT among higher education students.

Perceived Anthropomorphism and ChatGPT Behavioural Intention

Perceived Anthropomorphism is associated with human-like characteristics of human-like behaviour to non-human objects. It implies attributing human-like qualities, such as emotions and cognitive abilities (Airenti, 2015). For example, perceived anthropomorphism is applied in chatbot and digital assistant adoption (Balakrishnan et al., 2022; Sheehan et al., 2020). It was presumed that to improve users’ satisfaction, engagement, and positive evaluation on the use of intelligent systems, anthropomorphic characteristics are often effective (Lim et al., 2021). Meanwhile, the number of studies that look at whether perceived anthropomorphism has a positive impact on behavioural intention towards ChatGPT among higher education students is still limited, particularly using the UTAUT model. For example, Martin et al. (2020) reported that the user‘s attitude toward AI travel assistants has been improved with anthropomorphism features. They conclude that human-like characteristics can help to get users' acceptance of AI even in different user adoption settings. On the same note, Balakrishnan and Dwivedi (2024) also indicated that perceived intelligent and human like abilities can positively influence users' attitude. Recently, Polyportis and Pahos (2025) indicate that perceived anthropomorphism is a positive significant antecedent of users' attitude. Furthermore, Lee and Kim (2025) have empirically proven the idea of perceived anthropomorphism in human-AI interaction. They established that the users' attribution of human qualities to the chatbot has a powerful impact on users' psychological responses and engagement. On the basis of the aforementioned literature, this study formulates the following hypothesis:

H_6: There is a positive and significant relationship between perceived anthropomorphism and behavioural intention to use ChatGPT among higher education students.

Behavioural Intention (BI) and ChatGPT Usage

In the context of technology acceptance, Behavioural Intention (BI) is used to describe an individual's tendency in using technology for a particular purpose (Venkatesh et al., 2012; Venkatesh et al., 2003). Previous works reveal that BI is one of the most significant measures. It is a probable factor of actual usage behaviour. More specifically, higher BI will result in greater technology use (Budhathoki et al., 2024; Strzelecki, 2024). The behavioural intention is one of the core constructs in TAM and UTAUT, where BI can be affected by several factors, namely perceived usefulness, ease of use, performance expectancy, effort expectancy, social influence, and facilitating conditions. In this study, BI refers to the student's intention to use ChatGPT for a particular purpose, such as research, studying, and doing assignments. Examining BI is important to describe the acceptance of ChatGPT among students. Moreover, educators and developers can better understand how to introduce and implement the use of AI tools into teaching and learning scenarios. Based on the aforementioned findings, the subsequent hypothesis is proposed.

H_7: There is a significant positive relationship between behavioural intention and higher education students' usage of ChatGPT

METHODOLOGY

This study employed a quantitative, cross-sectional research design to investigate the predictors of ChatGPT adoption among higher education students. The quantitative approach is widely used in technology acceptance research for validating theoretical models and testing hypotheses using measurable constructs (Hair et al., 2022). A structured questionnaire was administered to capture students' perception on the extended UTAUT constructs. Five main activities are involved in the study, as elaborated further in the next subsections.

Population and Sampling Technique Selection

The respondents were selected among higher education students in Northern Malaysia, which comprised undergraduate and postgraduate students. They were chosen using a purposive and snowball sampling techniques (Bougie & Sekaran, 2025). Including students from different level of is essential, since the use of ChatGPT might vary between them. The higher education institution has a total of 30, 212 students, comprising 26, 398 undergraduate and 3, 814 postgraduate students (Teo, 2025). Based on a 95% confidence level and a ±5% sampling error, the minimum required sample size is approximately 384 respondents (Cohen, 2023).

Instrument Design

The questionnaire was developed by referring to the related works in the field, in three sections. The first section included screening questions to ensure that respondents have prior experience using ChatGPT. This is to ensure that the responses are relevant. The second section collected the demographic information, while the third section assessed interactions with ChatGPT using a 5-point Likert Scale (Bougie & Sekaran, 2025). The survey comprised 28 items assessing the constructs, as shown in Table 1.

Pilot Study

To increase the clarity and precision of the instrument, a pilot study was conducted, which was participated by 40 respondents. The Cronbach's Alpha value surpassed 0.7 for all constructs. This is considered sufficient following the suggestion of Hair et al. (2022). The questionnaire was revised again based on the results from the pilot test, so that it would fit the research objectives.

Data Collection

The questionnaire was distributed through learning platforms, communication channels, and student communities in the higher education institute by using an online questionnaire. The purpose of the study was explained to the participants, and they were assured that their responses would be kept confidential. Initially, 390 responses were collected. After screening, six (6) invalid questionnaires were eliminated. Finally, 384 responses were valid and selected for further analysis. The response rate is 97.5%, which is considered sufficient by previous studies (Holtom et al., 2022). As stated by Bujang (2023), the sample size of this study is considered sufficient. To ensure ethical compliance, this study has followed the general academic research protocols.

Data Analysis

SPSS and SmartPLS 4.1 were utilized to analyze the descriptive statistics and Partial Least Squares Structural Equation Modelling (PLS-SEM), respectively. The descriptive statistics provide an analysis of the respondents' demographics, including college, school, gender, educational level, frequency, use, purpose, and satisfaction with ChatGPT. A two-step PLS-SEM analysis was employed in this study. Firstly, the assessment of the measurement model was conducted to ensure reliability and validity. The reliability of the constructs was determined by Cronbach's Alpha and Composite Reliability (CR), while Average Variance Extracted (AVE) and indicator loadings were used to assess the convergent validity. Furthermore, the discriminant validity was examined through the Heterotrait-Monotrait Ratio (HTMT) and cross-loadings examination. Secondly, the assessment of the structural model was conducted to test the hypothesized relationship and overall model fit (Holtom et al., 2022). To examine the relationships among PE, EE, SI, FC, PI, and PA, and their influence on BI and UB, correlational analysis was used. The significance of each relationships were determined through the path coefficients, t-values, and p-values, which were obtained through bootstrapping. Moreover, to assess the model fit, the Standardized Root Mean Square Residual (SRMR) was employed. The explanatory power was determined through R-squared (R^2).

Table 1

Resources for Instrument Development

Constructs	Items	Questions	References
Performance Expectancy	PE1	ChatGPT helps me to complete tasks more efficiently.	Polyportis & Pahos (2025); Venkatesh et al. (2012); Venkatesh et al. (2003)
	PE2	ChatGPT simplifies my coursework.	
	PE3	ChatGPT proves beneficial for my classwork.	
Effort Expectancy	EE1	I find it easy to learn how to use ChatGPT.	
	EE2	I can easily make ChatGPT perform as I need it.	
	EE3	My interactions with ChatGPT are straightforward to comprehend.	
	EE4	I can quickly become proficient at using ChatGPT.	
Social Influence	SI1	My lecturers provide helpful guidance for using ChatGPT.	
	SI2	My lecturers encourage the use of ChatGPT for class.	
	SI3	The university, in general, supports the use of ChatGPT.	
Facilitating Conditions	FC1	I possess all the necessary resources to use ChatGPT.	
	FC2	I have the required knowledge to use ChatGPT.	
	FC3	ChatGPT fits seamlessly into my workflow.	
Perceived Intelligence	PI1	ChatGPT is proficient in delivering services.	Balakrishnan & Dwivedi (2024); Bartneck et al. (2009)
	PI2	ChatGPT demonstrates knowledge during interactions.	
	PI3	ChatGPT shows responsibility during service engagements.	
	PI4	ChatGPT has intelligent functions designed for services.	
Perceived Anthropomorp-hism	PA1	ChatGPT feels natural and not artificial.	Balakrishnan et al. (2022); Sheehan et al. (2020); Bartneck et al. (2009)
	PA2	ChatGPT behaves in a more human-like manner.	
	PA3	ChatGPT seems aware of its actions	
	PA4	ChatGPT seems lifelike rather than robotic.	
Behavioural Intention	BI1	I intend to use ChatGPT in my studies whenever feasible.	Polyportis & Pahos (2025); Venkatesh et al. (2012); Venkatesh et al. (2003)
	BI2	I intend to use ChatGPT over the next three months.	
	BI3	I intend to use ChatGPT for various tasks, including both academic and non-academic purposes.	
	BI4	I would use ChatGPT in my studies as frequently as possible.	
Use Behaviour	UB1	I use the free version of ChatGPT.	
	UB2	I use ChatGPT as an AI-powered writing assistant.	
	UB3	I use ChatGPT to produce work for my class assessments.	

RESULTS

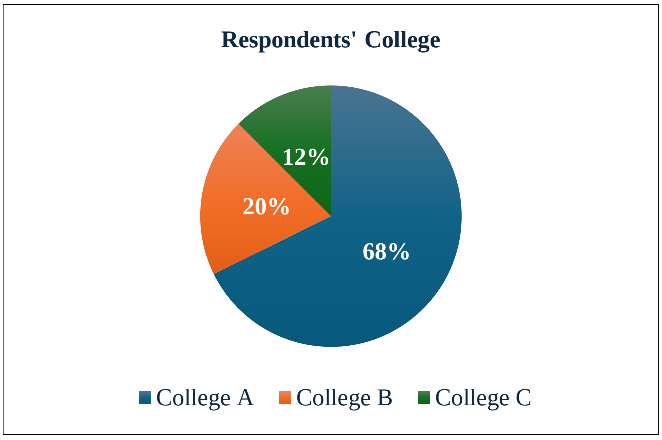
This section presents the results of the study, beginning with an explanation of the respondents' demographic profiles, followed by the evaluation of the measurement model and the assessment of the structural model. Each component is discussed in detail in the subsequent subsections.

Demographic of Respondents

The respondents were from multiple colleges and schools. The majority of them were from College A, which comprises technical and scientific-related programs, with 260 respondents (68%). This is followed by a total of 76 respondents (20%) from College B, which consists of business and management-related programs. College C, which comprises law and governance schools, had the lowest participation rate, with 48 respondents (12%). The respondents' college is illustrated in Figure 2.

Figure 2

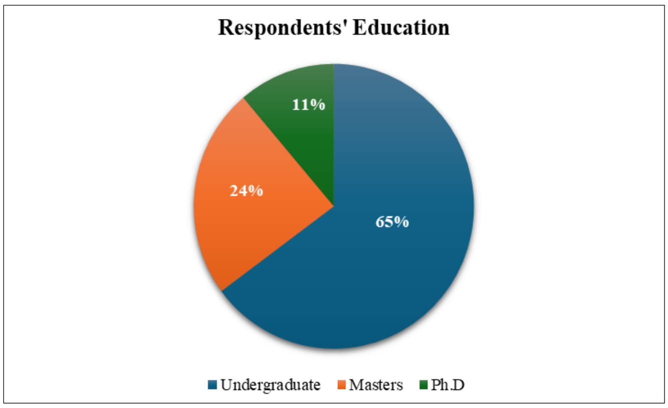
Respondents' College



The respondents were mostly undergraduate students (65%). The remaining were Master's students (24%) and PhD students (11%). These are demonstrated in Figure 3.

Figure 3

Respondents' Education Level



A large percentage of the respondents are male (59%). The remaining are 41% of female respondents. Moreover, most of the respondents are under 21 years old (168 respondents, 44%), followed by those aged 21 to 30 (152 respondents, 40%). The rest fall within the age groups of 31 to 40 (54 respondents, 14%), 41 to 50 (7 respondents, 2%), and above 50 (3 respondents, 1%). These are illustrated in Figure 4.

Figure 4

Respondents' Age Group

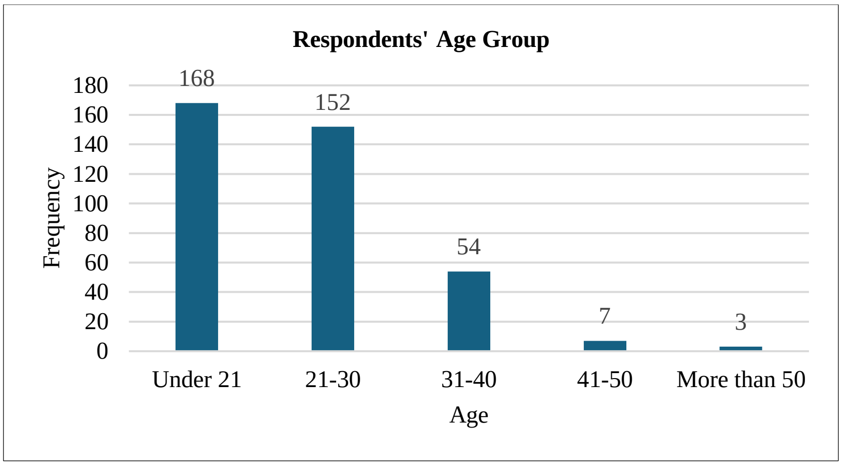


Table 2 summarizes respondents' experience with ChatGPT. Usage frequency varied, where majority of the respondents (51.56%) used it daily, 20.05% used it weekly, 17.97% used monthly, and 10.26% used it whenever needed. Furthermore, the most common purposes were research or learning (28.65%), writing or editing text (21.09%), creativity or brainstorming (18.49%), and problem solving or explanation (17.97%). Smaller proportions use it for study planning, personal development, or task automation. Regarding satisfaction, 57.03% were satisfied, 32.03% neutral, 7.03% very satisfied, and a minority expressed dissatisfaction (3.9%). Screening questions on college, education level, and ChatGPT experience ensured that participants were higher education students with prior ChatGPT usage.

Table 2

Respondents' Experience with ChatGPT

Questions	Option	Frequency	Percentage (%)
Frequency of ChatGPT usage	One or more times per day	198	51.56
	One or more times per week	77	20.05
	Once a month	69	17.97
	Whenever thinking of ChatGPT	40	10.26
The purpose of using ChatGPT	Research or learning	110	28.65
	Write or edit text	81	21.09
	Creativity, inspiration, or brainstorming	71	18.49
	Problem-solving and explanation	69	17.97
	Study planning and organization	25	6.51
	Personal development (career, etc.)	24	6.25
	Automation of simple tasks	4	1.04

(continued)

Questions	Option	Frequency	Percentage (%)
ChatGPT satisfaction	Satisfied	219	57.03
	Neutral	123	32.03
	Very satisfied	27	7.03
	Dissatisfied	11	2.86
	Very dissatisfied	4	1.04

Evaluation of the Measurement Model

Table 3 shows that the measurement model demonstrates strong reliability and validity across all constructs. Performance Expectancy (α = 0.89; CR = 0.93; AVE = 0.81), Effort Expectancy (α = 0.89; CR = 0.93; AVE = 0.77), Social Influence (α = 0.91; CR = 0.93; AVE = 0.81), Facilitating Conditions (α = 0.84; CR = 0.93; AVE = 0.81), Perceived Intelligence (α = 0.80; CR = 0.93; AVE = 0.76), Perceived Anthropomorphism (α = 0.88; CR = 0.93; AVE = 0.77), Behavioural Intention (α = 0.90; CR = 0.94; AVE = 0.79), and Use Behaviour (α = 0.92; CR = 0.95; AVE = 0.86) all exhibited high reliability. Factor loadings ranged from 0.83 to 0.96 for all items. This exceeds suggested 0.7 threshold, indicating adequate indicator reliability. The AVE values confirm convergent validity across constructs (Hair et al., 2022; Fornell & Larcker, 1981). Overall, the results indicate that the constructs are reliable and the measurement model is robust for subsequent structural analysis. Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio. Table 4 depicts the result, where all values are below the recommended 0.85 threshold. Additionally, the square root of each construct's AVE exceeded its correlations with other constructs. It further supports discriminant validity (Henseler et al., 2015). Overall, the measurement model demonstrates adequate reliability and validity. Thus, it provides a solid foundation for testing the structural model.

Table 3

Measurement Model Results

Constructs	Items	Factor loading	Cronbach-α	Composite Reliability (CR)	Average Variance Extracted (AVE)
PE	PE1	0.95	0.89	0.93	0.81
	PE2	0.88			
	PE3	0.87			
EE	EE1	0.95	0.89	0.93	0.77
	EE2	0.85			
	EE3	0.86			
	EE4	0.85			
SI	SI1	0.95	0.91	0.93	0.81
	SI2	0.90			
	SI3	0.85			
FC	FC1	0.95	0.84	0.93	0.81
	FC2	0.88			
	FC3	0.87			
PI	PI1	0.95	0.80	0.93	0.76
	PI2	0.83			
	PI3	0.84			
	PI4	0.87			

(continued)

Constructs	Items	Factor loading	Cronbach-α	Composite Reliability (CR)	Average Variance Extracted (AVE)
PA	PA1	0.95	0.88	0.93	0.77
	PA2	0.85			
	PA3	0.85			
	PA4	0.86			
BI	BI1	0.96	0.90	0.94	0.79
	BI2	0.85			
	BI3	0.88			
	BI4	0.87			
UB	UB1	0.95	0.92	0.95	0.86
	UB2	0.92			
	UB3	0.90			

Table 4

Haterotrait-Monotrait Ratio (HTMT) Ratio

	BI	EE	FC	PA	PE	PI	SI	UB
BI								
EE	0.427							
FC	0.452	0.336						
PA	0.466	0.253	0.364					
PE	0.54	0.261	0.278	0.257				
PI	0.407	0.284	0.263	0.301	0.204			
SI	0.474	0.261	0.276	0.289	0.253	0.306		
UB	0.44	0.148	0.159	0.166	0.199	0.24	0.238	

Structural Model Assessment

Once the measurement model was confirmed, the structural model was assessed. Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), which was 0.039 for the saturated model and 0.04 for the estimated model. Both are below the recommended threshold of 0.08, which indicates a satisfactory fit (Hu & Bentler, 1999). Multicollinearity among constructs was assessed using the Variance Inflation Factor (VIF), where values above 10 indicate serious multicollinearity. All VIF values in this study were within acceptable limits, as depicted in Table 5. They confirm that multicollinearity is not a concern and ensure the robustness of the structural model for further analysis (Henseler et al., 2015).

Table 5

Outcomes of Collinearity Diagnostics

Path Relationships	VIF
BI -> UB	1.000
EE -> BI	1.192
FC -> BI	1.243
PA -> BI	1.224
PE -> BI	1.141
PI -> BI	1.183
SI -> BI	1.185

Hypothesis testing indicates that all seven proposed relationships are supported, as depicted in Table 6. Performance Expectancy significantly influenced Behavioural Intention (H_1: β = 0.303, p = 0.000), as did Effort Expectancy (H_2: β = 0.149, p = 0.000) and Social Influence (H_3: β = 0.209, p = 0.000), highlighting that adoption is driven by how much the tool helps users achieve tasks more effectively or efficiently. Moreover, it suggests that even advanced AI tools must remain intuitive to encourage sustained user engagement, and it is often socially driven. Facilitating Conditions (H_4: β = 0.148, p = 0.001) and Perceived Intelligence (H_5: β = 0.135, p = 0.001) had smaller yet significant effects, suggesting that access, support, and perceived cognitive competence encourage usage. Perceived Anthropomorphism (H_6: β = 0.182, p = 0.000) positively influenced intention, indicating that human-like characteristics enhance adoption. Behavioural Intention strongly predicted Use Behaviour (H_7: β = 0.406, p = 0.000). Collectively, the predictors explained 48.3% of the variance in Behavioural Intention (R^2 = 0.483) and 16.5% of the variance in Use Behaviour (R^2 = 0.165). Although the model captures key drivers of students' intention to adopt ChatGPT, additional factors are needed to explain actual usage better, for instance, situational, institutional, or ethical considerations.

Table 6

Hypotheses Testing Results

Hypothesis	Path Relationships	β	SE	t-value	p-value	LLCL	ULCL	f^2	R^2	Decision
H_1	PE -> BI	0.303	0.043	7.030	0.000	0.214	0.384	0.155		Supported
H_2	EE -> BI	0.149	0.042	3.566	0.000	0.068	0.231	0.036	0.483	Supported
H_3	SI -> BI	0.209	0.042	4.931	0.000	0.126	0.293	0.071		Supported
H_4	FC -> BI	0.148	0.045	3.307	0.001	0.061	0.233	0.034		Supported
H_5	PI -> BI	0.135	0.039	3.454	0.001	0.058	0.211	0.030		Supported
H_6	PA -> BI	0.182	0.042	4.314	0.000	0.100	0.265	0.052		Supported
H_7	BI -> UB	0.406	0.042	9.577	0.000	0.323	0.488	0.197	0.165	Supported

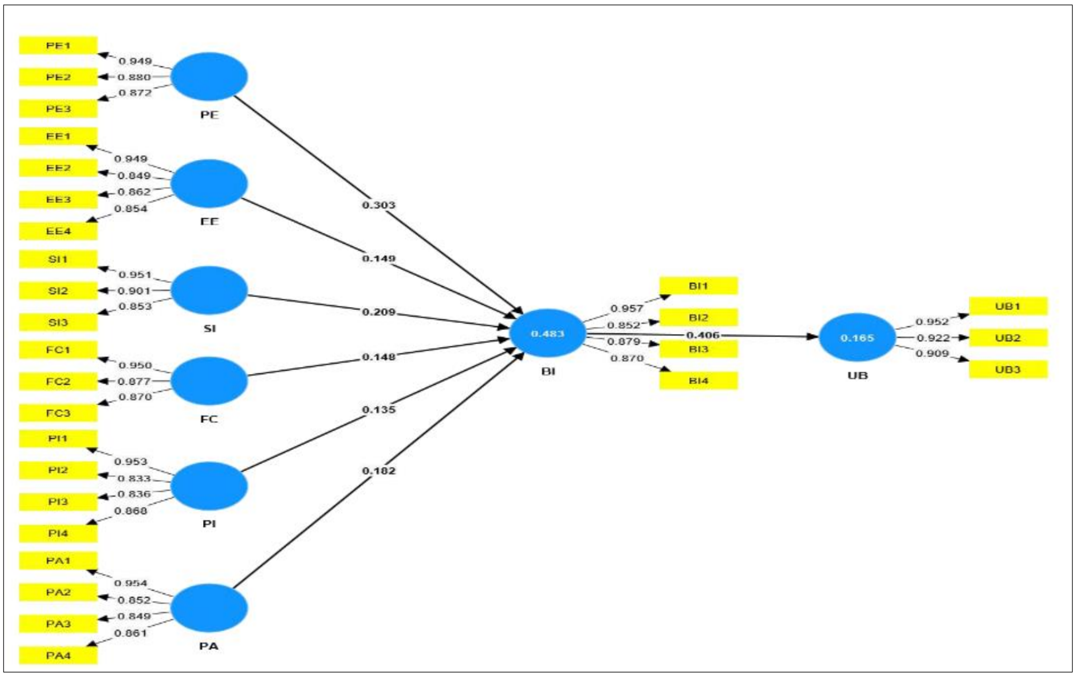
Based on the explained hypothesis results, the formula for BI is as follows:

$$BI=0.303(PE)+0.149(EE)+0.209(SI)+0.148(FC)+0.135(PI)+0.182(PA)$$
$$UB=0.406(BI)$$

Figure 5 presents the PLS-SEM results of the proposed ChatGPT usage behavioural model, including the path coefficients and explained variances (R^2 values) of the endogenous constructs. The model shows that all of the six predictors significantly influence Behavioural Intention, which predicts actual Use Behaviour of ChatGPT.

Figure 5

PLS Algorithm Results



DISCUSSION

This study examined the factors that influence ChatGPT adoption among higher education students by extending the UTAUT model with Perceived Intelligence and Perceived Anthropomorphism. It offers theoretical and empirical results on the use of generative AI in learning environments.

Influence of Performance Expectancy on Behavioural Intention to Use ChatGPT

Performance Expectancy (PE) was a significant predictor of Behavioural Intention (BI). This result is consistent with prior technology acceptance research (Polyportis & Pahos, 2025; Siddiqui et al., 2025; Namatovu & Kyambade, 2025; Strzelecki, 2024; Gansser & Reich, 2021; Venkatesh et al., 2003). Probably, students prefer to adopt ChatGPT if they find that it can increase their performance in academics, improving their understanding of course materials, or increasing efficiency in assignments and research tasks. This underscores that the perceived academic value of ChatGPT such as generating explanations, summarizing readings, or providing immediate feedback directly strengthens students' intention to use it. This outcome is supported by recent studies which emphasize that generative AI is most appealing when it assists concrete learning needs and productivity (Polyportis & Pahos, 2025; Siddiqui et al., 2025; Budhathoki et al., 2024).

Influence of Effort Expectancy on Behavioural Intention to Use ChatGPT

Effort Expectancy (EE) was also found to be a significant predictor of Behavioural Intention (BI). ChatGPT's intuitive interface, natural language processing, and minimal learning curve reduce the cognitive effort required to use the tool, making it accessible even without technical expertise. This ease of use enhances students' willingness to integrate ChatGPT into academic tasks. The finding is consistent with preceding research, which highlights that learners desire educational technologies that are simple and user-friendly (Budhathoki et al., 2024; Strzelecki, 2024; Gansser & Reich, 2021). The conversational nature of ChatGPT further enhances perceived ease of use, which increases adoption intentions. Nevertheless, some studies report contradictory results (Owan et al., 2025; Shittu & Taiwo, 2023). This is possibly because students with heavy workloads or limited time may be less inclined to try new tools compared to established study methods (Owan et al., 2025).

Influence of Social Influence on Behavioural Intention to Use ChatGPT

Social Influence (SI) had a moderate but meaningful effect on Behavioural Intention (BI). Students were motivated to use ChatGPT through recommendations from peers, lecturers, academic communities, and social media. Its widespread visibility across digital platforms normalizes usage and reinforces its credibility as an academic support tool. Consistent with prior research, social influence enhances curiosity, encourages experimentation, and increases adoption (Namatovu & Kyambade, 2025; Owan et al., 2025; Budhathoki et al., 2024; Gansser & Reich, 2021). In university settings, SI indicates that using ChatGPT is acceptable, beneficial, and aligned with emerging academic norms.

Influence of Facilitating Conditions on Behavioural Intention to Use ChatGPT

Facilitating Conditions (FC) significantly influenced Behavioural Intention (BI). This result indicates that the availability of technical resources and institutional support promotes AI adoption. More importantly, access to reliable internet, personal devices, and university-led digital literacy initiatives enhances students' ability to use ChatGPT effectively. Such supportive environments enable the incorporation of generative AI into learning activities. The previous studies also point out similar findings. This shows that the institutional readiness and infrastructural support for adopting educational technologies are essential to promote ChatGPT usage (Polyportis & Pahos, 2025; Budhathoki et al., 2024; Strzelecki, 2024).

Influence of Perceived Intelligence on Behavioural Intention to Use ChatGPT

Perceived Intelligence (PI) emerged as one of the significant predictors of BI. This indicates the importance of system capability in influencing student adoption. Students exhibited their interest in using ChatGPT when they found it to be a highly knowledgeable, logical, and cognitively capable system that could provide accurate and academically relevant responses, which enhanced their trust in using it. Trust in AI is closely connected to perceived intelligence. The students would rely more on the tool when the outputs appear coherent and authoritative (Chaves & Gerosa, 2021; Madsen & Gregor, 2000). This finding supports the emerging research indicating that perceived cognitive competence is central to the adoption of generative AI tools like ChatGPT, especially in academic settings (Balakrishnan & Dwivedi, 2024).

Influence of Perceived Anthropomorphism on Behavioural Intention to Use ChatGPT

Perceived Antromorphism (PA) significantly influences Behavioural Intention (BI). It highlights that higher education students would prefer to adopt the tool when it exhibits human-like features, such as natural interaction and responsiveness. In educational contexts, these features enhance social presence, trust, and engagement. These make ChatGPT easier and more appealing to use. The result aligns with recent research, which suggests that human-like attributes in conversational AI positively affect user attitudes, engagement, and adoption (Lee & Kim, 2025; Balakrishnan & Dwivedi, 2024; Polyportis & Pahos, 2025). The findings emphasize the value of anthropomorphic design in promoting students' academic use of ChatGPT.

Influence of Behavioural Intention on Use Behaviour of ChatGPT

Behavioural Intention (BI) showed a significant positive effect on actual Use Behaviour (UB). This result supports the notion that intention predicts usage, as proposed by TAM and UTAUT (Venkatesh et al., 2012; Venkatesh et al., 2003). Recent studies on generative AI adoption also confirm that students with higher intention would choose to use ChatGPT for academic tasks such as drafting assignments, coding, research, organizing notes, and exam preparation (Budhathoki et al., 2024; Strzelecki, 2024). These results highlight that BI is a reliable predictor of actual use. On top of that, it highlights the motivational, perceptual, and contextual factors in translating intention into engagement with ChatGPT. The findings indicate that ChatGPT has become an influential learning tool among higher education students. The use of ChatGPT enhances their engagement with academic tasks, fostering technological skills, and supporting lifelong learning. Students found that ChatGPT is valuable for self-learning, understanding complex concepts, and completing assignments, projects, and research activities. Its ability to provide instant explanations, generate structured content, and guide problem-solving promotes independent and efficient study. The tool's accessibility and intuitive interface also encourage experimentation with emerging technologies. It can improve digital fluency and readiness for AI-driven academic and professional environments.

Despite its benefits, the study highlights important concerns related to academic integrity. If students rely too much on ChatGPT, it may affect authenticity and ethical conduct. Responsible use of ChatGPT among students is affected by their personal values and institutional guidance. Thus, there is a need for clear academic policies, digital literacy initiatives, and ethical awareness. If students are appropriately guided, ChatGPT can support learning and creativity without replacing students' own intellectual effort. Additionally, ChatGPT promotes lifelong learning by encouraging curiosity, self-directed inquiry, and continuous knowledge acquisition. Its conversational nature enables students to explore ideas, clarify concepts, and develop adaptive learning strategies that extend beyond formal education. ChatGPT is not only an academic support tool but also a tool that supports lifelong learning.

Overall, the study concludes that ChatGPT serves as a powerful educational companion that enhances academic performance, nurtures technological exploration, and promotes ongoing learning, provided that its use is guided by strong ethical practices and institutional support. This study suggests that universities need to guide the evaluation of AI-generated information to avoid over-reliance on tools that are highly intelligent like ChatGPT.

CONCLUSION

In conclusion, this study has extended the UTAUT model by incorporating Perceived Intelligence and Perceived Anthropomorphism. The result effectively explains students' acceptance and use of ChatGPT in the higher education context. All six predictors significantly influence Behavioural Intention, which predicts actual Use Behaviour. The results of two constructs, Perceived Intelligence and Perceived Anthropomorphism, highlight the critical role of students' perceptions of ChatGPT's cognitive and human-like capabilities. These findings emphasize that to enhance engagement and adoption, AI tools must not only be functional but also perceived as intelligent and relevant. Despite these insights, the study has limitations, which are the cross-sectional nature of the study and its focus on a particular higher education institution. These may restrict the generalizability. Future research could employ longitudinal and comparative studies across disciplines or different AI platforms, incorporate behavioural analytics to supplement self-reported data, and examine ethical and pedagogical implications, such as academic integrity and students' critical thinking. Overall, the study contributes to the literature on AI adoption by validating an extended UTAUT model for generative AI and provides practical guidance for universities, educators, and AI developers to support the use of ChatGPT in educational settings.

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