Exploring Academic Intentions for ChatGPT: A Perspective from the Theory of Planned Behavior

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ABSTRACT

Advancements such as OpenAI's ChatGPT are part of cutting-edge megatrends in artificial intelligence (AI). ChatGPT has the potential to reshape education. This article applies the Theory of Planned Behavior (TPB) to investigate the correlation between attitude, subjective norms, perceived behavioral control, and the inclination to utilize ChatGPT for academic purposes. Our methodology involved conducting an online cross-sectional survey of 311 university students in Malaysia, a majority Malaysian (82.3%) and female (61.1%) aged 21-23 (66%). We develop three hypotheses and test them with SmartPLS 4. The results suggest that attitude, perceived behavioral control, and subjective norms exert a positive influence on the intention to embrace ChatGPT. From a pragmatic standpoint, it is advisable for universities to actively incorporate AI technologies like ChatGPT into the academic setting, addressing attitudes, subjective norms, and perceived control to prepare students effectively.

Keywords: Academic setting, ChatGPT, Intention to use, Attitude, Subjective norms, Perceived behavioral control.

INTRODUCTION

ChatGPT, an advanced artificial intelligence (AI) chatbot designed to respond to text-based requests, was introduced by OpenAI on November 30, 2022 and amassed one million users within just five days. As of November 2023, the platform boasts approximately 1.5 billion monthly visits and a user base exceeding 180 million (Duarte, 2023). OpenAI, motivated by the aim of creating a friendly AI for the benefit of humanity (OpenAI, 2023), trained its language model based on the GPT-3.5

architecture (Homolak, 2023). GPT-4, an enhanced version, became available to ChatGPT Plus users on March 14, 2023, featuring substantial performance improvements and multimodal generation capabilities (OpenAI, 2023).

ChatGPT has significantly influenced various sectors including education (Cotton et al., 2023; Ray, 2023). ChatGPT has also sparked considerable research interest by scholars and researchers, particularly regarding its applications for education (Choudhury & Shamszare, 2023; Gundu, 2023; Lund & Wang, 2023; Rudolph et al., 2023; Shoufan, 2023). ChatGPT can furnish 24/7 real-time feedback and deliver personalized learning experiences for students through tailored materials (Firat, 2023; Lund & Wang, 2023). Furthermore, ChatGPT can play a pivotal role in bridging global education gaps and contributing to the democratization of education by enhancing the accessibility of educational resources (Farrokhnia et al., 2023; Firat, 2023). Students have found ChatGPT user-friendly and appreciate its human-like interface, which provides well-structured responses and clear explanations (Shoufan, 2023). It has also demonstrated its capacity to enhance student engagement and collaboration (Cotton et al., 2023). Early adopters of ChatGPT view this technology as a revolutionary leap that has the potential to bolster students' self-efficacy and motivation to learn (Mogavi et al., 2023). Beyond educational purposes, the application of ChatGPT extends to areas such as information gathering, entertainment, and problem-solving (Choudhury & Shamszare, 2023).

However, there is significant concern about the potential overreliance on AI generative tools like ChatGPT, a trend that could cultivate superficial learning habits and diminish students' social and critical thinking skills (Mogavi et al., 2023). There is also apprehension that these tools may impede creativity and critical thinking by offering convenient solutions to assignments and interview questions (Dwivedi et al., 2023; Malik et al., 2023; Qureshi, 2023). Students have expressed reservations about the accuracy of ChatGPT's responses, underscoring the need for a solid foundation of background knowledge to use it effectively, as it cannot replace human intelligence (Shoufan, 2023). Significantly, the generation of articulate sentences based on extensive datasets poses challenges in detecting plagiarism in academic work (Cotton et al., 2023; Ray, 2023; Rudolph et al., 2023). This capability of ChatGPT raises concerns about the integrity of academic assessments and the potential for students to disengage from traditional university experiences and feedback mechanisms (Choudhury & Shamszare, 2023; Qureshi, 2023). Furthermore, the responsibility to assess and validate new content generated by ChatGPT falls on both teachers and students (Lund & Wang, 2023). Such content may inadvertently contain misinformation and perpetuate stereotypes due to biases in the training data and the lack of accountability by the AI (Choudhury & Asan, 2022; Smith, 2021). When comparing teacher and student attitudes to ChatGPT, students are more optimistic of ChatGPT's role in education and are generally less critical of its application for academic purposes (Waltzer et al., 2023).

Given the potential benefits of ChatGPT, including enhanced learning experiences and global accessibility, accompanied by concerns such as overreliance, potential erosion of critical thinking, and accuracy issues, the intricate landscape of AI generative tools is evident. IT is therefore vital to identify the factors influencing the adoption of ChatGPT. Understanding these factors will not only facilitate the responsible integration of this technology into educational settings but also contribute to maximizing its benefits while mitigating potential challenges.

Many scholars are studying ChatGPT using various technological adoption theories, including the Theory of Planned Behavior (TPB). This theory is widely accepted and has been long employed to understand technology adoption. TPB is based on three fundamental constructs: attitude, subjective norms, and behavioral control. This theory offers a comprehensive framework for elucidating the factors that influence user preferences and inclinations toward a specific technology (Ajzen, 1991).

Utilizing TPB to elucidate user behavior, researchers have shed light on the determinants of intentions and usage of AI chatbot technology (Jo, 2023), as well as the exploration of information security behaviors within the context of ChatGPT (Gundu, 2023).

While these pioneering studies have offered valuable insights into the factors influencing the intention to use ChatGPT, drawing upon TPB, their results do not represent the perspectives of Asian students regarding the use of ChatGPT for academic purposes. The current study aims to address notable gaps in the existing literature, especially with the emergence of ChatGPT in education, warranting closer examination. It seeks to contribute to the existing body of knowledge by investigating the behavioral intention to use ChatGPT for academic purposes, utilizing TPB and reassessing the previously established associations between its constructs in a different context—Malaysia, an early technology adopter (Toh, 2017), and where the integration of AI in education is being discussed by authorities (Bernama, 2024).

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

THEORY OF PLANNED BEHAVIOR

Among various technology adoption theories, TPB has been identified as the fourth-most-frequently utilized theory (Salahshour Rad et al., 2018). TPB, introduced by Ajzen (1991), holds a prominent position as a widely recognized framework in the realm of social cognition. TPB is an extension of the Theory of Reasoned Action (TRA) model that focuses on two variables: attitudes and subjective norms. Attitude is defined as a positive or negative feeling in relation to the achievement of an objective while subjective norms refer to the very representations of the individuals' perception in relation to the ability of reaching those goals with a given product. These two factors influence the intention to perform behaviors (Armitage & Conner, 2001). While the TRA could adequately predict behaviors that were relatively straightforward (i.e., under volitional control), under circumstances where there were constraints on action, the mere formation of an intention was insufficient to predict behavior (Armitage & Conner, 2001). Therefore, TPB was created to overcome this inadequacy by incorporating a measure of perceived behavioral control as an additional determinant of intentions (Armitage & Conner, 2001), in order to provide a more comprehensive understanding of both volitional and non-volitional behaviors (Ajzen, 1991; Hagger & Hamilton, 2020). Perceived behavioral control denotes a person's expectation that performance of the behavior is within his/her control (Ajzen, 2020).

In TPB, three constructs, namely attitude, subjective norms and perceived behavioral intention, elicit behavioral intention. According to Ajzen (1991; 2020), behavioral intentions constitute the fundamental and immediate precursors of human actions. Behavioral intention refers to an individual's inclination to either perform or refrain from a specific action (Ajzen & Fishbein, 1975). TPB explains how individuals make intentional decisions by carefully weighing the advantages and disadvantages of their anticipated actions before putting them into practice (Ajzen, 2020).

The versatility of TPB extends to explaining a spectrum of behaviors that demand thoughtful preparation. Moreover, TPB's relevance extends to technology acceptance, where it has been extensively utilized in numerous fields (Ajzen, 2020), including learning and teaching. For example, TPB was appreciated to study the adoption of m-learning (Yeap et al., 2016), e-learning (Hadadgar et al., 2016), virtual reality (Al Breiki et al., 2023), and many more.

In the next section of the literature review, we will review the associations between TPB constructs and the behavioral intention to adopt various technologies in the field of learning and teaching. Moreover, we will specifically explore existing yet limited literature regarding the applications of TPB to investigate the behavioral intention of AI generative tools, including ChatGPT.

ATTITUDE

Attitude mirrors individuals' cognitive and affective assessment of a specific behavior (Ajzen, 1991). The formation of attitudes is grounded in the expectancy-value formulation, a fundamental concept for understanding how attitudes develop (Ajzen, 2020; Fishbein & Ajzen, 1975). Individuals shape their attitudes toward an object based on their beliefs about that object, and these beliefs are shaped through the association of specific attributes with the object (Ajzen, 1991). Positive attributes are linked to favorable attitudes, whereas negative attributes tend to result in unfavorable attitudes (Ajzen, 1991; 2020). Attitude has been shown to be a predictor of adoption for various novel technologies such as wearable devices like smartwatches (Acikgoz et al., 2023; Elnagar et al., 2022) and AI applications (Chen, 2023).

Regarding the relationship between attitude and intention to adopt technology in the field of education and learning, there is a growing body of evidence suggesting that a positive attitude toward the integration of technology in learning and teaching is a driving force behind the intention to adopt technology (Anthony et al., 2020; Lee et al., 2010; Rahmat et al., 2022). For example, Cabero-Almenara et al. (2022) demonstrated that a high level of acceptance of augmented and virtual reality technologies among students is positively linked to their favorable attitudes toward using these technologies and their intention to utilize them. Similarly, Garcia & Oducado (2021) discovered that a positive attitude toward mobile game-based learning predicts the behavioral intention to employ this information and communications technology to mitigate the negative effects of policies aimed to mitigate the effects of a pandemic on teaching and learning. Attitude emerges as a consistent significant predictor of the use of virtual reality in the science classroom among teachers (Al Breiki et al., 2023). Users' attitudes were identified as a significant predictor of the intention to adopt AI-based robots in the educational system of Indian universities (Roy et al., 2022). Additionally, the attitudes of Chinese university students toward Massive Open Online Courses (MOOCs) significantly influenced their acceptance of these platforms (Zhou, 2016). The acceptance of digital learning innovations through augmented reality applications among students could also be explained by their attitudes, suggests Batool (2022). Attitude also emerged as a strong determinant of digital library resource adoption among medical students during the COVID-19 outbreak (Rahmat et al., 2022). Moreover, attitude was found to predict the intention to use educational technology among Chinese-as-a-second/foreign-language teachers (Sun & Mei, 2022).

Recent research has indicated that learners with favorable attitudes toward the utility of ChatGPT are more likely to exhibit a heightened behavioral intention to utilize ChatGPT for English learning beyond the classroom (Liu & Ma, 2023). Another study delved into the influential role of attitude in shaping the adoption of the AI chatbot, ChatGPT, among a sample of university students (Jo, 2023). Furthermore, attitude emerged as a predictive factor for investigating information security behaviors using ChatGPT (Gundu, 2023). Based on this literature, the following first hypothesis (H1) is proposed: *There is a significant relationship between attitude toward using ChatGPT for academic purposes and behavioral intention to use it.*

SUBJECTIVE NORM

Subjective norms refer to the perceived social pressure on individuals to engage in specific behaviors (Ajzen, 1991). These shared beliefs held by individuals or groups can significantly shape people's intentions (Ajzen, 1991). Subjective norms are influenced by a person's normative beliefs combined with the person's motivation to comply. Normative beliefs are concerned with the likelihood that important others would approve or disapprove of a behavior, and motivation to comply is an assessment of how important it is to have the approval of others (Ajzen, 1991).

As technology continues to advance and gain widespread adoption, researchers have shifted their focus to investigating subjective norms as a significant factor influencing the acceptance of technology in teaching and learning. For instance, Lai et al. (2022) conducted a study showcasing the considerable impact of subjective norms on students' intention to utilize mobile technology in language learning classrooms. Similarly, Cheon et al. (2012) found that the readiness of college students to adopt mobile devices for coursework is reasonably well explained by subjective norms. Additionally, subjective norms were identified as having a notable effect on Chinese students' attitudes toward Internet-based technology for educational purposes (Huang et al., 2020). Subjective norms also played a crucial role as predictors of the intention to incorporate augmented reality in engineering education, as evidenced by Álvarez-Marín et al. (2023). Batool (2022) emphasized the role of subjective norms in elucidating students' acceptance of digital learning innovations through augmented reality applications. Furthermore, subjective norms indirectly influenced the intention to use Google apps, which were employed in designing a learning environment for project work and learning (Rejón-Guardia et al., 2020). Similarly, Kim et al. (2021) found that subjective norms positively influence students' acceptance of online learning systems in higher education. However, low scores on perceived innovativeness can mitigate the strength of this influence.

Subjective norms shape both pre-service and in-service teachers' intentions to use technology in Turkey (Ursavaş et al., 2019). Subjective norms also impact the integration of technology during teaching practice, including placement or practicum, among Indonesian pre-service teachers (Habibi et al., 2023). Consistent research findings indicate a positive relationship between social norms and the intention to use virtual reality, particularly among science teachers (Al Breiki et al., 2023). In Al Kurdi et al.'s study (2021), subjective norms were established as significant motivating factors for students using social media networks for educational purposes. Likewise, Wang et al. (2023) identified subjective norms as crucial determinants influencing teachers' intentions regarding the use of MOOCs. Subjective norms also exerted influence on the intention to use digital library resources among medical students during the COVID-19 outbreak (Rahmat et al., 2022).

Recent research has paved the way in investigating the relationship between subjective norms and information security behaviors employing ChatGPT (Gundu, 2023), as well as the utilization of the AI chatbot, ChatGPT (Jo, 2023). Ofosu-Ampong et al. (2023) also explored the impact of social influence on the acceptance or rejection of AI tools, such as ChatGPT, in education. Based on this literature, we propose the following second hypothesis (H2): *There is a significant relationship between subjective norms and behavioral intention to use ChatGPT for academic purposes.*

PERCEIVED BEHAVIORAL CONTROL

Perceived behavioral control encompasses an individual's assessment of the ease or difficulty associated with executing a specific behavior (Ajzen, 1991). This assessment considers factors such as resource availability and the necessary skills for task execution (Ajzen, 2020). This concept closely corresponds to perceived self-efficacy, which involves an individual's evaluation of the effort required to perform an action in a given situation (Ajzen, 1991).

The impact of perceived behavioral control has garnered substantial endorsement across diverse fields including the adoption of technology in the field of learning and education. For instance, Al Breiki et al. (2023) identified perceived behavioral control as a factor associated with the implementation of virtual reality in science classrooms by teachers. Similarly, Garcia & Oducado (2021) observed that perceived behavioral control influences the intention to incorporate mobile game-based learning among nursing teachers. In the context of university students, perceived behavioral control predicts the adoption of mobile learning platforms for accessing course materials, searching the web for information related to their disciplines, sharing knowledge, and submitting assignments, especially during the COVID-19 pandemic (Akour et al., 2021). This predictive role of perceived behavioral control extends to intentions to use MOOCs among Chinese students (Niu, 2019) and the adoption of Moodle in students from Macau (Teo et al., 2019).

Transitioning from the exploration of perceived behavioral control in learning and education to its significance in the realm of AI chatbots, such as ChatGPT, we observe that the concept remains a pivotal factor in shaping user intentions and adoption. Shoufan (2023) observed that students appreciate ChatGPT's capabilities, find it user-friendly, and value its human-like interface, which delivers well-structured responses and clear explanations despite occasional inaccuracies. Another study also identified perceived behavioral control as a precursor to the intention to use the AI chatbot among a sample of university students (Jo, 2023). Duong et al. (2023) consistently found that higher education students' use of ChatGPT for learning is influenced by their belief in the ease of use of ChatGPT. Based on the above literature, we put forth the following third hypothesis (H3): *There is a significant relationship between perceived behavioral control and behavioral intention to use ChatGPT for academic purposes.*

METHOD

RESEARCH DESIGN AND DATA COLLECTION PROCEDURE

In the current study, we used quantitative research methods, rooted in deductive reasoning, and associated with positivism, where the researchers hold an ontological perspective that seeks objective understanding and the existence of absolute truth (Creswell, 2018). This method is primarily employed to test or confirm existing theories and postulates (Creswell, 2018). There are two main designs in quantitative research methods: experimental and survey. In this study, we employed a survey design, specifically a cross-sectional approach, which has the advantage of measuring current attitudes or practices at a single point in time without manipulation (Ary et al., 2018). We obtained ethical approval from Xiamen University Malaysia's Research Ethics Board [REC Ref. No.: REC-2304.02], ensuring compliance with ethical considerations.

We collected the required data from university students in Selangor district, Malaysia, which is an urban area. Participants who met the inclusion criteria (being university students, having some experience with using ChatGPT for academic purposes, such as generating entire essays, solving mathematical problems, and obtaining answers to queries in academic assignments and homework) and confirmed that they had read and understood the provided information, and agreed to participate in this study voluntarily, were allowed to proceed and complete the survey.

The survey consisted of several sections with a cover page where participants were presented with the objectives of the study and its ethics principles. The first section covered demographic details and the following sections consisted of survey questions. Soliciting information for the variables under investigation. Google Forms was used for data collection. Using Google Forms facilitated our efficient data collection, offering accessibility, automatic recording, and easy distribution via e-mail or social media. Two research assistants shared the survey link within their university networks, ensuring broad participation. Data collection took one and a half months, from April 1 to May 15, 2023.

In this study, we used Structural Equation Modeling (SEM) to test structural relationships. Several absolute numbers have been suggested as a rule of thumb for sample size over several decades. However, there is no single absolute number that can be used with complete confidence (Memon et al., 2022). Some researchers often rely on "rules of thumb." A group of statistics scholars has recommended using the ratio of observations-to-estimated parameters (N:q) as a guide. For instance, Kline (2015) suggests a 20-to-1 sample-to-item ratio, meaning 20 respondents for each item in the survey questionnaire.

The survey consisted of 12 questions, encompassing both independent and dependent variables. The calculation of 20 multiplied by 12 equals 240, confirming the need for 240 participants, as specified by Kline's (2015) rule of thumb. In addition to the rules of thumb, a group of scholars suggested that a sample between 160 and 300 valid observations is usually well-suited for Partial Least Square (PLS)-SEM (Memon et al., 2022). We followed the latter suggestion in the present study. In total, 311 responses used for data analysis met this suggestion.

PARTICIPANTS

A total of 311 participants took part in the present study. Among them, 61.1 percent were female, 37.3 percent were male, and five percent preferred not to reveal their gender. The majority of participants (66 percent) fell into the 21-23 age category (M = 21.36, SD = 1.51). An overwhelming percentage of participants identified as Malaysian (82.3 percent). With a small margin, 46.9 percent of participants reported having average intelligence, while 44.7 percent perceived their intelligence level as good. Similarly, 43.1 percent reported feeling somewhat satisfied with their performance, and 40.5 percent reported being satisfied with their performance. Additionally, 42.2 percent reported occasionally using ChatGPT for academic purposes, such as generating entire essays, solving mathematical problems, and obtaining answers for academic assignments and homework. Furthermore, 31.8 percent reported frequent usage of ChatGPT. The details of the demographic characteristics of the participants are displayed in table 1.

Table 1

Demographic profile of participants (N = 311).

Variables	N (%)	Variables	N (%)
Gender		**Age**	
Male	116 (37.3%)	18-20	82 (26.3%)
	190 (61.1%)	21-23	205 (66%)
	5 (1.6%)	24-27	24 (7.7%)
Female			
Prefer not to answer			
Nationality		**Perceived intelligence**	
Malaysian	256 (82.3%)	Excellent	17 (5.5%)
Indonesian	17 (5.5%)	Good	139 (44.7%)
China	34 (11%)	Average	146 (46.9%)
Others	4 (1.2%)	Poor	9 (2.9%)
Perceived performance		**The use of ChatGPT for academic purposes such as generating entire essays, solving mathematical problems, and getting answers to queries in academic assignments and homework**	
Very satisfied	26 (8.4%)	Always	32 (10.3%)
Satisfied	126 (40.5%)	Frequently	99 (31.8%)
Somewhat satisfied	134 (43.1%)	Occasionally	132 (42.4%)
Unsatisfied	19 (6.1%)	Rarely	48 (15.5%)
Very unsatisfied	6 (1.9%)		32 (10.3%)

MEASUREMENTS

The items used to measure the four constructs of TPB, i.e., attitude, perceived behavioral control, subjective norms, and behavioral intention, were adopted from Cheon et al.'s (2012) study. All items underwent a process of adaptation to adapt to the particularities of our research (Heggestad et al., 2019). Each construct was examined by three items. All items were rated on a 5-point Likert Scale from 1 = strongly disagree, to 5 = strongly agree. The detailed list of items is presented in table 2.

DATA ANALYSIS

The TPB model was analyzed through PLS modeling with SmartPLS version 4 (Ringle et al., 2022) being used to determine the relationship between attitude, subjective norms, perceived behavioral control, and behavioral intention to use ChatGPT for academic purposes. We analyzed data in two stages. First, we validated the model via the measurement model. Second, we developed the structural model using a 5,000 resampling of bootstrapping to determine the significant associations between the measured construct.

RESULTS

MEASUREMENT MODEL

Firstly, we validated the scales used in this study in the measurement model. All four scales that measured the four TPB constructs were assessed in terms of their loadings, reliability, convergent validity using average variance extracted (AVE) and discriminant validity using Heterotrait-Monotrait (HTMT) ratio of the correlation. In this study, the loadings of all items for all scales ranged between .830 to .916, above .70 as recommended by Hair et al. (2019), thus all items were retained. All constructs showed good reliability and composite reliability values are above .70. All constructs also showed good convergent validity as all the AVE values were above .50 (see table 2).

Table 2

Measurement items, factor loadings, AVE and CR

Constructs/items	Loadings	AVE	CR
Behavioral intention to use ChatGPT		0.762	0.905
I predict that I would use ChatGPT for academic purposes in the next six months.	0.888		
My future plans involve using ChatGPT for academic purposes.	0.896		
I intend to use ChatGPT for academic purposes in the future.	0.833		
Attitude toward ChatGPT		0.754	0.902
Using ChatGPT for academic purposes is a wise idea.	0.869		
ChatGPT makes my assignments and homework better and more impressive.	0.830		
I like working with ChatGPT for academic purposes.	0.905		
Subjective norms		0.831	0.937
People who influence my behavior think I should use ChatGPT for academic purposes.	0.910		
People who are important to me think that I should use ChatGPT for academic purposes.	0.909		
In general, my lecturers have supported the use of ChatGPT for academic purposes.	0.916		
Perceived behavioral control		0.721	0.886
It would be easy for me to become skillful and knowledgeable at using ChatGPT for academic purposes.	0.861		
I have a sufficient extent of control to make a decision to use ChatGPT for academic purposes.	0.836		
I am confident that I can use ChatGPT for academic purposes.	0.851		

Note: AVE = Average Variance Extracted; CR = Composite reliability.

The discriminant validity was also assessed using the HTMT ratio of the correlation as recommended by Henseler et al. (2015). To achieve discriminant validity, the HTMT values should be below .90. As shown in table 3, all HTMT values in our study were below .90, showing that all participants understood that all constructs are distinct.

Table 3

Discriminant validity using HTMT.

Constructs	1	2	3	4
1. Behavioral intention to use ChatGPT				
2. Attitude toward ChatGPT	0.871			
3. Subjective norms	0.706	0.753		
4. Perceived behavioral control	0.822	0.892	0.666	

STRUCTURAL MODEL

Based on the measurement model, all four scales that measured the TPB's constructs (i.e., behavioral intention to use ChatGPT, attitudes toward ChatGPT, subjective norms and perceived behavioral control) have good reliability and validity, thus we proceeded to test the hypotheses in the structural model. First, multicollinearity assumption was assessed using the variance inflation factors (VIF). All VIF values were below 5, therefore the multicollinearity assumption was not violated. A bootstrapping of 5,000 resampling was conducted to test the relationship between attitude toward using ChatGPT, subjective norms, perceived behavioral control, and behavioral intention to use ChatGPT for academic purposes.

As shown in table 4, we found that individuals' attitude toward using ChatGPT for academic purposes ($\beta = .437$, $P < .001$), subjective norms ($\beta = .184$, $P = .003$) and perceived behavioral control ($\beta = .279$, $P < .001$) have significant positive relationship with their behavioral intention to use ChatGPT for academic purposes, supporting all three hypotheses. Overall, attitudes toward using ChatGPT, subjective norms and perceived behavioral control together predicted 64.2 percent of variance in the behavioral intention to use ChatGPT.

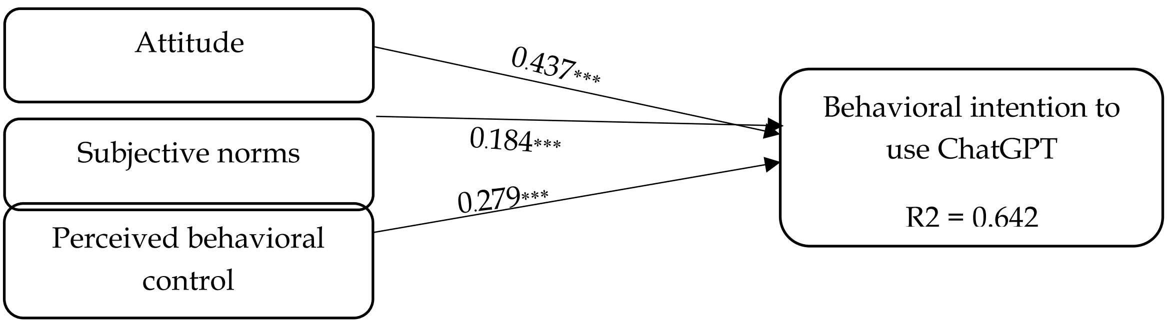
Table 4

Hypotheses testing direct effects.

Hypothesis	Paths	Beta	t-value	P-value	BCI LL	BCI UL	VIF
H1	Attitude → Behavioral intention	0.437	5.584	<0.001	0.303	0.560	2.666
H2	Subjective norms → Behavioral intention	0.184	2.762	0.003	0.081	0.303	1.717
H3	Perceived behavioral control → Behavioral intention	0.279	3.996	<0.001	0.162	0.390	2.271

Figure 1

*Path coefficient of the structural research model, whereby *** means $P < 0.001$.*



Furthermore, PLS-Predict was conducted using a 10-fold procedure to check for predictive relevance. Shmueli et al. (2019) suggested a strong predictive power if all items in the PLS-SEM model were lower than the LM model (Linear Regression Model). Based on table 5, all the prediction errors in the PLS-SEM model were lower or equal to the LM model, thus our model has a strong predictive power.

Table 5

PLS-Predict.

Item	PLS_RMSE	LM_RMSE	PLS-LM	Q^2 predict
Behavioral intention 1	0.988	0.998	-0.010	0.498
Behavioral intention 2	0.967	0.967	0	0.540
Behavioral intention 3	0.999	1.000	-0.001	0.527

DISCUSSION

The study delves into the integration of ChatGPT, a cutting-edge technology, in educational settings, aligning with previous research affirming TPB's impact on technology acceptance (Chai et al., 2020; Gundu, 2023; Jo, 2023; Niu, 2019).

RELATIONSHIP BETWEEN ATTITUDE AND BEHAVIORAL INTENTION

Our findings corroborate a strong positive relationship between attitude and intention (H1), consistent with broader technology adoption research (Acikgoz et al., 2023; Chen, 2023; Rahmat et al., 2022). Notably, attitude emerged as a key determinant, echoing its significance in TPB (Ajzen, 1991). This aligns with research emphasizing attitude's determinant role in ChatGPT adoption (Jo, 2023; Liu & Ma, 2023), resembling its impact on blended learning intention (Anthony et al., 2020) and virtual reality use in the science classroom (Al Breiki et al., 2023). Positive attitude links to perceived usefulness, driven by hedonic motivations (Strzelecki, 2023), shaping a favorable view of ChatGPT's application beyond the classroom (Liu & Ma, 2023). In agreement with these findings, Ma & Huo's (2023) research demonstrated evidence that affective attitudes significantly reduce objections to ChatGPT, and cognitive attitudes are the primary antecedent of customers' willingness to accept ChatGPT. Additionally, the contributory role of positive attitudes toward the usefulness of ChatGPT was found to elevate the actual use of ChatGPT in English learning outside the classroom (Liu & Ma, 2023).

Perceived skills readiness and trust further strengthen the attitude-intention relationship (Al Breiki et al., 2023; Chaudhry et al., 2023), underscoring the importance of these two constructs in strengthening or mitigating the correlation coefficient between attitude and intention. Similarly, the determining role of trust was identified in Choudhury & Shamszare's (2023) research in shaping ChatGPT users' adoption.

The technology's positive impact on engagement, collaboration, and accessibility contributes to the overall positive attitude toward ChatGPT (Cotton et al., 2023). Similarly, Tiwari et al. (2023) explored how usefulness, social presence, and legitimacy of the tool, as well as enjoyment and motivation, contribute to a favorable attitude among students toward using ChatGPT. These insights emphasize the importance of cultivating positive attitudes in enhancing the intention to use ChatGPT in educational contexts.

RELATIONSHIP BETWEEN SUBJECTIVE NORMS AND BEHAVIORAL INTENTION

Subjective norms prove integral in shaping the intention to use ChatGPT for academic purposes (H2). This result substantiates the utmost importance of a person's interpretation of social norms for action and their personal evaluation of the possible consequences of the action under consideration (Conner & Armitage, 1998), as observed in the current study regarding the deployment of ChatGPT for academic execution. The current study lends credibility to documented influences on technology adoption (Batool, 2022; Huang et al., 2020; Rahmat et al., 2022; Wang et al., 2023). For instance, subjective norms were identified as an antecedent of adaoption of MOOCs by teachers (Wang et al., 2023), the appreciation of digital library resources by students (Rahmat et al., 2022), the use of augmented reality in engineering education (Álvarez-Marín et al., 2023), and Google apps for learning (Rejón-Guardia et al., 2020).

This study reiterates the significance of subjective norms as determinants of intention for ChatGPT's academic applications (Gundu, 2023; Jo, 2023). It also provides support for Ofosu-Ampong et al.'s (2023) research finding that social influence predicts acceptance of AI in education. All these findings across diverse educational technologies and specifically the use of innovative tools like ChatGPT unfailingly reinforce the contribution of an individual's perception of social expectations to adopt a particular technology.

RELATIONSHIP BETWEEN PERCEIVED BEHAVIORAL CONTROL AND BEHAVIORAL INTENTION

Behavioral control emerges as the second significant factor influencing the intention to use ChatGPT (H3), validating Ajzen's (2020) perspective on people's perceived ease and difficulty of performing the behavior. The actionality of the behavior is, in fact, subject to individuals' competencies and the environmental facilitating conditions (Ajzen, 2020). In other words, if supportive conditions exist, individuals are more likely to have a stronger behavioral intention to perform an action. In Ajlouni et al.'s study (2023), a group of participants reported feeling uncomfortable utilizing the platform and experiencing anxiety when unable to access ChatGPT's services. These two factors could influence students' decisions to use ChatGPT.

The finding of the present study aligns with previous research on technology adoption (Akour et al., 2021; Garcia & Oducado, 2021; Niu & Mvondo, 2024; Teo et al., 2019). For instance, perceived behavioral control plays a role in shaping teachers' intention to embrace VR in science classrooms (Al Breiki et al., 2023), forming students' adoption of mobile learning platforms for accessing course materials (Akour et al., 2021), and facilitating mobile game-based learning among nursing teachers (Garcia & Oducado, 2021).

The user-friendliness of ChatGPT and its human-like interface contributes to its perceived ease of use (Shoufan, 2023), echoing its impact on the intention to use (Duong et al., 2023; Jo, 2023). Ma & Huo (2023) explored how novelty value and perceived humanness increase consumers' performance expectancy (the belief that using the system can help gain benefits in activities) and decrease effort expectancy (the convenience and usability when using a specific information system) regarding ChatGPT. In a related study, Liu & Ma (2024) demonstrated that perceived ease of use predicts a positive attitude toward the use of ChatGPT in the informal digital learning of English among English-as-a-foreign-language learners, mediated through the perceived usefulness of this technology. This aligns with Duong et al.'s (2023) findings that the ease of using ChatGPT positively influences higher education students' intention and actual usage for learning purposes.

IMPLICATIONS

The present study makes several theoretical contributions to existing knowledge. Firstly, our findings contribute to the emergent body of research on the determinants of intention to use ChatGPT, within the framework of TPB. The results of the present study also provide practical implications for educators and educational institutes, encouraging them to create a pedagogically effective and ethically responsible AI-integrated learning environment. The present study demonstrated that favorable attitudes, subjective norms, and perceived behavioral control are the determining factors for university students to adopt ChatGPT for academic purposes. Educators are encouraged to conduct training sessions providing professional exposure to ChatGPT's use in academia, fostering positive attitudes and enhancing perceived control. A positive attitude toward ChatGPT indicates favorability, contributing to a more enjoyable and satisfactory user experience, which makes individuals more likely to intend to use the technology and fosters continued use and adoption (Liu & Ma, 2023; Roy et al., 2022). Moreover, attitude includes emotional responses (Ajzen, 2020), which can strongly influence decision-making (Armitage & Conner, 2001). A positive emotional connection to ChatGPT enhances the likelihood of adoption. Therefore, an emphasis on a positive attitude toward the use of ChatGPT in academia can be leveraged in successful ChatGPT training programs.

Educational institutions can offer technical support to help students navigate challenges, thereby strengthening perceived behavioral control, which involves perceived ease of use (Shoufan, 2023). If users feel that interacting with ChatGPT is within their control and capabilities, they are more likely to adopt it. Furthermore, higher perceived behavioral control is associated with greater self-efficacy (Ajzen, 1991; 2020), contributing to users' confidence in their ability to successfully engage with ChatGPT. Understanding perceived behavioral control can also help in identifying and addressing potential barriers to adoption, ensuring a smoother user experience.

Creating hands-on experiences with ChatGPT contributes to fostering positive student attitudes. Educators should launch awareness campaigns highlighting the technology's benefits, including providing real-time feedback, delivering personalized learning experiences, enhancing engagement and collaboration, and boosting self-efficacy and motivation for problem-solving (Choudhury & Shamszare, 2023; Cotton et al., 2023; Firat, 2023; Mogavi et al., 2023). Simultaneously, educators need to address the potential risks associated with ChatGPT, such as fostering superficial learning habits, diminishing critical thinking skills, and perpetuating stereotypes due to biases in the training data (Choudhury & Asan, 2022; Mogavi et al., 2023). This balanced approach ensures that students are equipped with a comprehensive understanding of both the advantages and challenges posed by the integration of ChatGPT in educational settings.

Providing platforms for students to share diverse experiences about ChatGPT, whether positive or negative, can shape social norms, supporting or challenging AI generative tool use in academic settings. Subjective norms capture the influence of social factors on individual intentions (Ajzen, 2020). If users perceive that important others such as friends, teachers or peers approve or encourage the use of ChatGPT, it positively impacts their intention to adopt. The use of AI generative tools can become a normative expectation. Aligning with societal expectations and norms can contribute to a sense of acceptance and legitimacy, influencing the decision to adopt ChatGPT (Ofosu-Ampong et al., 2023). Research showed that positive subjective norms can lead to word-of-mouth recommendations (Perera et al., 2020), creating a network effect and increasing the likelihood of widespread adoption. Understanding all these factors can help educators and AI tool developers invest in the right elements to cultivate a specific culture of AI tool acceptance.

Identifying the factors that influence the adoption of ChatGPT is also crucial for the development of user-friendly and successful AI systems in education system (Shoufan, 2023). It can also empower the developers to enhance the design and functionality of ChatGPT and improve the user experience. Knowledge on the influence of TPB elements on the adoption of ChatGPT is also equally important for securing market acceptance, enabling businesses to opt for and tailor their marketing strategies, identifying target audiences, and locate ChatGPT effectively in a competitive landscape. Moreover, this awareness influences the creation of effective educational and training programs for users and developers.

LIMITATIONS AND RECOMMENDATION FOR FUTURE RESEARCH

This study's cross-sectional design limits causal inference (Creswell, 2018). In the current cross-sectional study, data was collected at a single point in time, providing a snapshot of the samples' opinions and viewpoints about the use of ChatGPT. Consequently, it becomes challenging to determine the sequence of events or to discern cause-and-effect relationships. Therefore, longitudinal studies are recommended, involving data collection at multiple time points, allowing for a more comprehensive examination of temporal relationships and facilitating a stronger basis for drawing causal conclusions. Data from students in urban areas may lack generalizability (Ary et al., 2018), emphasizing the need for diverse samples. Relying solely on data from urban areas introduces a potential limitation as it may not accurately represent the broader population's characteristics and perspectives. Therefore, to enhance the external validity of the findings and ensure a more comprehensive understanding, it is recommended for future research to include participants from diverse backgrounds, encompassing rural, suburban, and urban settings. By incorporating a more inclusive sample, future researchers can better capture the nuances of various demographics, thereby strengthening the study's validity and increasing its relevance to a wider range of communities and settings.

Future studies could integrate insights from other important psychological, educational and ethical theories. By incorporating relevant theories, researchers can provide a more comprehensive framework for understanding the underlying mechanisms and implications of the phenomena under investigation. Psychological theories could shed light on the cognitive and emotional aspects, offering a nuanced perspective on individual behaviors and responses. Simultaneously, educational theories could contribute insights into pedagogical strategies, learning processes, and the impact on academic outcomes. This holistic integration of psychological, educational and ethical theories would not only broaden the research's theoretical foundation but also foster a more robust and multi-dimensional exploration of the subject matter, potentially yielding richer insights and practical implications for both academia and real-world applications. In the present study, our focus was on examining behavioral intention to use rather than actual use. Consequently, unexplored links between behavioral intention and actual behavior in ChatGPT use prompt a critical inquiry into the translation of strong intentions into practical usage, warranting further investigation.

CONCLUSION

In conclusion, the current study strongly corroborates the credibility of TPB in facilitating assessment criteria for the acceptance of ChatGPT among university students. It has established the significance of the three components of TPB as predictors of the intention to use ChatGPT among university students. Our findings reveal that attitude emerges as the most influential factor shaping the intention to use ChatGPT, underscoring the pivotal role of individual perceptions and positive attitudes in driving acceptance. Moreover, perceived behavioral control was identified as another crucial predictor, emphasizing the importance of users' perceived ability to control and navigate their interactions with ChatGPT. Lastly, subjective norms were identified as a positive predictor, indicating the influence of social perceptions and approval in shaping the intention to adopt ChatGPT. In summary, the behavioral intention to adopt ChatGPT involves the multifaceted nature of user decision-making driven by multiple factors, including attitude, perceived behavioral control, and subjective norms. These factors should be given weight in the design, implementation, and promotion of such technologies within educational settings.

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