The effects of awareness and trust on students' willingness to use ChatGPT: an integrated TAM-ECM model

Efectos de la conciencia y confianza en la disposición estudiantil para usar ChatGPT: modelo TAM-ECM integrado

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ABSTRACT

Although the use of ChatGPT in the educational field has spread rapidly in universities, there is little information on factors affecting students' intentions toward using ChatGPT to support their learning. This study bridges the gap by integrating the extended Technology Acceptance Model (TAM) (including awareness and trust) with Expectation Confirmation Model (ECM) constructs, namely confirmation and satisfaction. This proposed model provides an in-depth understanding of students' willingness to use ChatGPT. Data was collected from 322 university students and analyzed using a second-generation analysis technique, Structural Equation Modeling (SEM) using AMOS. The results revealed that awareness significantly positively affected students' perceived usefulness (PU) and perceived ease of use (PEU). Furthermore, trust had a significant positive effect on PU, but an insignificant effect on PEU. In addition, PU, PEU, and confirmation significantly positively affected students' satisfaction, affecting their behavioral intention toward using ChatGPT for their learning. Furthermore, PU and PEU significantly positively affected students' behavior intention toward using ChatGPT. This study offers recommendations to developers of ChatGPT, policymakers, and educational institutes by understanding the influential factors on students' willingness to use ChatGPT. This study assists ChatGPT developers and designers by offering insight regarding designing and improving the user's secure and friendly system, which may enhance the use of ChatGPT among students.

Keywords: ChatGPT; TAM; ECM; satisfaction; awareness; trust.

RESUMEN

Aunque el uso de ChatGPT en el ámbito educativo se ha expandido rápidamente en las universidades, se conoce poco sobre los factores que influyen en la intención de los estudiantes de utilizar esta herramienta para apoyar su aprendizaje. Este estudio aborda esa brecha integrando el Modelo de Aceptación de la Tecnología (TAM), ampliado con las variables de conciencia y confianza, y el Modelo de Confirmación de Expectativas (ECM), con los constructos de confirmación y satisfacción. El modelo propuesto profundiza en la comprensión de la disposición de los estudiantes a utilizar ChatGPT. Se recopilaron datos de 322 estudiantes universitarios, analizados mediante Modelado de Ecuaciones Estructurales (SEM) con AMOS. Los resultados revelaron que la conciencia influye significativamente y de forma positiva en la utilidad percibida (PU) y en la facilidad de uso percibida (PEU). Además, la confianza mostró un efecto positivo sobre la PU, pero no impactó de manera relevante la PEU. Asimismo, la PU, la PEU y la confirmación afectaron positivamente la satisfacción de los estudiantes, la cual incide en su intención de utilizar ChatGPT. Por otro lado, tanto la PU como la PEU tuvieron un efecto positivo significativo en la intención de uso (BI) de la herramienta. El estudio ofrece recomendaciones para desarrolladores, responsables de políticas educativas e instituciones académicas, orientadas a comprender y fomentar la adopción de ChatGPT. Además, aporta información valiosa para mejorar el diseño y la seguridad del sistema, favoreciendo una experiencia amigable para el usuario y promoviendo su uso en el ámbito educativo.

Palabras clave: ChatGPT; Modelo de Aceptación de la Tecnología (MAT); Modelado de Ecuaciones Estructurales (MES); satisfacción; conciencia; confianza.

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INTRODUCTION

Integrating Artificial intelligence (AI) and information and communication technologies (ICT) led to innovations that radically changed the education landscape (Kelly et al., 2023). The quick rise of AI has increased its use in our daily lives. Chatbot is an example of an AI system widely used as an intelligent human-computer interaction (HCI) (Bansal & Khan, 2018). Even though chatbots could provide entertainment and simulate a human conversation, their aims extend beyond that (Iku-Silan et al., 2023). Chatbots are used in many sectors, such as business, information retrieval, e-commerce, and education (Ismail et al., 2024). OpenAI, a company that produced a new version of Chatbot, ChatGPT, was established on November 30, 2022. Since then, it has attracted over 1 million subscribers (Baidoo-Anu & Owusu Ansah, 2023). ChatGPT is a large language model (LLM) that uses machine learning to research vast text data deeply and produce intelligent and sophisticated writing. ChatGPT, along with other LLMS users, has already been used by professionals and researchers to deliver speeches and write essays, review papers, summarize literature, spot research gaps, and author programs to conduct statistical analysis (van Dis et al., 2023). Four different versions of ChatGPT were considered with different parameters specifically ChatGPT-1 including 117 million parameters, ChatGPT-2 included 1.5 million parameters, ChatGPT-3 included 175 million parameters, and ChatGPT-4 includes 100 trillion parameters. The parameters have been incremented by this, to give the ChatGPT-r an unmatched performance level of text generation similar to human speech (OpenAI, 2023). In other words, ChatGPT could also create documents and research papers in different tones and styles (Lund & Wang, 2023).

Besides, ChatGPT could analyze and evaluate large quantities of textual data, for example, examining new articles and social media posts and enabling understanding of several languages with machine translations. The automated summarizing capabilities of ChatGPT could be used to inform the researchers about the latest advancements and developments in fields that are related to them. Furthermore, ChatGPT is a helpful tool for giving researchers timely and domain specific answers without the need for any facilitators (Lund & Wang, 2023). ChatGPT can help and support researchers with a variety of research activities in different disciplines (Frieder et al., 2023; Haleem et al. 2022). As ChatGPT becomes famous and with a clear interest in ChatGPT's applications, students want to use it in many different areas. Students can use ChatGPT for its assistance in their academic work to help in figuring out the ideas or concepts they were taught in learning works (van Dis et al. 2023). ChatGPT can be considered a reference application for students' knowledge fields and studies as it can be used to gather knowledge and information about various topics (Cao et al., 2023). ChatGPT is utilised by students to provide insight into some topics, get extra explanations for some complex topics, and solve their academic challenges (Lund & Wang, 2023). As ChatGPT has 24/7 access and immediate response requests, students use it for easy and quick access to knowledge and information (Baidoo-Anu & Owusu Ansah, 2023).

While several studies have been conducted to assess the role of ChatGPT in educational fields (e.g., Al-Sharafi et al., 2023; Rudolph et al., 2023; Alshammari & Alshammari M. H., 2024), there is a lack of studies assessing the acceptance and adoption of ChatGPT (Bin-Nashwan et al., 2023; Bernabei et al., 2023). In addition, Rahman (2023) conducted a study on ChatGPT based on reviewing 787 studies in

Scopus database records where only few studies were about students' adoption and acceptance of ChatGPT. In addition, many of these previous studies were limited to developed countries, for instance in the UK and the US, while there were limited studies conducted in a developing country (i.e. the Kingdom of Saudi Arabia). In addition, although most of the studies were centred around relevant technologies e.g. cloud computing and new virtual realities (Sestino & D'Angelo, 2023), there may be differences among cultures and technologies when accepting and adopting new technologies (Ashraf et al., 2019). Furthermore, contrary to the fact that ChatGPT could potentially pose a huge benefit for students that could support their learning process, it is imperative to have a thorough knowledge of which factors could influence their intention to utilise it. Al-Sayid and Kirkil (2023) point out that the Technology Acceptance Model (TAM) is a popular model of educational foundation that investigates how users think about different technologies and how they use and perceive these technologies. According to TAM, the perceived usefulness (PU) and the perceived ease of use (PEU) are two basic ingredients involved in the uptake of technological systems (Davis, 1989). In fact, the TAM model is not operated in isolation of these two main factors, rather, there could be other external factors that will explain the effect of these two main factors (Abdalla, 2024). Other external factors that could affect the utilization of ChatGPT are awareness and trust in using ChatGPT. Awareness refers to familiarity with a specific technology and the benefits associated with using it (Mutahar et al., 2018). Before using an application such as ChatGPT, students first have to know about it. The nature of ChatGPT, the benefits of it and educating students in regards to ChatGPT can greatly change how students respond to the understanding of ChatGPT. In addition, trust is users' belief in the credibility and reliability of technology (Arpaci, 2016). Trust can be a crucial factor affecting the adoption and acceptance of new technologies (Liu & Tao, 2022). Moreover, as proposed by Bhattacherjee (2001), the Expectation Confirmation Model (ECM) is widely used to assess the influential factors that affect users' continued use of a specific technology. It contains three main constructs: perceived usefulness, confirmation, and satisfaction.

Although there has been a great interest in using ChatGPT in institutions and universities, little research has been conducted to assess the causal relationships that affect students' intention to use ChatGPT in their studies (Yu et al., 2024). Thus, this study aims to fill the existing research gap and identify the key factors that could affect students' utilization of ChatGPT in their learning. It will propose a theoretical model by combining the extending TAM to incorporate external factors, namely trust and awareness, and assess ECM model factors, namely confirmation, and satisfaction. Based on our knowledge, this is the first study that combines extended TAM (with the additional constructs of awareness and trust) with an ECM model to assess the factors that could affect students' intention toward using ChatGPT.

Literature review and hypothesis development

ChatGPT is a chatbot based on a model of large-scale (Schulman et al., 2022). ChatGPT is different from other AI models as it uses a conceptual model similar to humans' brains to react to issues with natural language understanding. ChatGPT is considered a valuable asset in several fields, including academic research, writing, poetry writing, testing activities, and software development business communication (Tung, 2023). With the quick technological advancement and global integration, AI

ChatGPT is now widely used in universities to provide efficient, cost-effective approaches to motivating and engaging students with personalized learning experiences (Polyportis, 2024; Albayati, 2024). While ChatGPT is powered by AI generation, it has been rapidly evolving as it has the potential to take part in the education revolution. The education industry has begun using several tools and technologies to enhance learning and teaching activities and increase classroom efficiency. One of these important aspects that could support the learning and teaching activities is ChatGPT. Some research has been carried out by several researchers to assess the practicability of the utilisation of ChatGPT in the field of education, such as in research related to the practical utilisation of ChatGPT in professional and educational academic activities (Brown et al., 2020; Emenike & Emenike, 2023) and ChatGPT to aid in language learning (Alshammari & Alshammari M. H., 2024). Because ChatGPT can offer rapid feedback on students' assignments, answer their questions, generate educational materials and materials, and prepare lesson plans, it could play a big role in supporting students' learning whilst giving them a personalized learning experience (Albayati, 2024).

Furthermore, it is necessary to take into consideration the adoption and acceptance of ChatGPT from students' perspectives (Patel & Lam, 2023). TAM has been widely used for decades to assess the adoption of different technologies (Venkatesh & Davis, 2000; Folkinshteyn & Lennon, 2016; Alshammari & Alshammari R. A., 2024). TAM is a theorized model framework that explains users' ways of adopting and accepting a new technology developed by Davis (1989). TAM has proved its applicability with several contexts and technologies as it has been tested with various technologies such as mobile apps, websites, and social media, demonstrating its reliability and validity (Alshammari & Alshammari R. A., 2024). Researchers have extended and modified TAM to explore the effects of additional factors, such as satisfaction, system quality, and personal innovativeness (Esposito et al., 2020; Alshammari & Alshammari R. A., 2024). Furthermore, ECM is another popular model developed by Bhattacherjee (2001). Since the establishment of ECM, it has been validated and used widely with various technologies such as digital textbooks (Joo et al., 2017), mobile apps (Tam et al., 2020), Facebook (Mouakket, 2015), and smart devices (Park,2020). Several studies recommended the integration of different models to assess the influential factors on the intention to utilize technologies (Huang & Zhi, 2023; Alshammari & Alshammari R. A., 2024) and to overcome some limitations associated with models (Wandira et al., 2024). While this study's main purpose is to deeply explore the factors that could affect students' intention to use ChatGPT for their learning, this study will integrate two models by extending TAM (including the two external factors: trust and awareness) and ECM.

Technology Acceptance Model (TAM)

TAM is a model developed by Davis in 1989. This model is used widely to explain users' interaction with various technologies. In the TAM model, PU and PEU are the main factors explaining the intention to utilise a technology (Davis, 1989). In addition, since the model's establishment, several constructs were incorporated into TAM as external factors to explain better and predict the influential factors on users' intention toward using information technologies (Nikou, S. A., & Economides, 2017). Within the context of AI applications, Mohr & Kühl (2021) extended TAM to include other factors, such as personal innovativeness and property rights in business data, to assess their effects on accepting AI in German agriculture. Li (2023) extended TAM and included learning motivation as an external variable to assess its effect on students' acceptance of AI intelligence systems. Xu et al. (2023) expanded TAM to assess the effects of technical features, previous experience and perceived Trust on users' intention to use AI painting applications. However, even though TAM and extended TAM have been used widely with many AI applications, the use of extended TAM with AI ChatGPT has received little attention. Furthermore, no study integrated the extended TAM with variables of awareness and trust with the ECM model to assess the influential factors on students' behavior and intention to use ChatGPT for their learning. Thus, this study proposes a theoretical model by integrating the extended TAM with the ECM model to clarify the factors influencing students' intention to use ChatGPT for their learning.

Expectation Confirmation Model (ECM)

ECM was developed by Bhattacherjee (2001). It explains how users repurchase intention. Since its establishment, it has been validated by researchers widely with the continuous use of several IS technologies, such as digital textbooks (Joo, 2017), Facebook (Mouakket. 2015), e-government (Hong et al., 2006), and learning management systems (Ashrafi et al., 2022). Based on ECM, PU and confirmation are the main variables that determine satisfaction, and satisfaction affects users' continuous intention toward using a technology. Some researchers integrated ECM with other models, for instance, with IS success model in a virtual classroom context (Alshammari & Alshammari R. A., 2024) and integrating ECM with self-determination in e-banking (Rahi et al., 2023) or ECM with TAM with the context of cloud-based academic system (Wandira et al, 2024). However, the integration of ECM with extended TAM (including the variables of awareness and trust as external factors) has not been applied to assess the influence on students' willingness to utilise ChatGPT for their learning. Thus, this proposed model contributes to the existing literature and provides a theoretically integrated model that explains the phenomena of accepting ChatGPT among students for their learning. The following section will elaborate on the research model and its related research hypothesis.

Research model

This study proposed a model that integrated extended TAM with additional variables, namely, awareness and trust, and ECM variables, namely satisfaction and confirmation, to assess the influential factors on students' intention to utilise ChatGPT. In the following parts, the model variables and their hypothesis are explained based on these two models and the literature review.

Awareness

Awareness is an essential critical predictor of accepting a technology. Users should be aware of the functionality, existence, and benefits of technology before adopting and accepting it. Within the ChatGPT context, awareness is related to understanding the applicability, limitations and capabilities (Eppler et al., 2024). Developing awareness among users is an essential step in accepting any technology. Users who are not aware of the benefits of ChatGPT might not consider accepting and using this technology

(Maheshwari, 2023). Despite assessing the effect of awareness in many different areas, such as in mobile banking (Mutahar et al., 2018), smart home assessability (Shuhaiber & Mashal, 2019), and AI services (Flavián et al., 2022), there is a lack of studies about the effect of awareness on PU and PEU in the context of ChatGPT. When users are aware and understand the capabilities and qualities of technology, they might consider that technology useful. Furthermore, when users know the huge benefits and capabilities of using ChatGPT to enhance their learning activities, they might perceive ChatGPT as easy to use. Thus, it is hypothesized as follows:

H1: Awareness positively affects PU.
H2: Awareness positively affects PEU.

Trust

Perceived trust stands for users' belief regarding technology's credibility and reliability (Arpaci, 2016). This trust could convince users to use a specific technology to meet their expectations and objectives (Liu & Tao, 2022). While AI applications have spread widely, users' trust in AI might play a small part in influencing their decision to accept and use them (Choung et al., 2023). The trust variable has been incorporated into the TAM model as an external factor. When users trust the credibility and reliability of ChatGPT, they will consider it useful. Similarly, when users trust the credibility and reliability of ChatGPT, they consider it easy to use. Thus, the following hypotheses are formulated:

H3: Trust in using ChatGPT positively affects PU.
H4: Trust in ChatGPT positively affect PEU

Perceived Ease of Use (PEU)

PEU refers to the level at which users believe a piece of technology is free from effort (Davis, 1989). Within the ChatGPT context, it might involve the easier interaction of students and educators with ChatGPT and integrating ChatGPT with their educational activities (Baek & Kim, 2023). Some empirical studies confirmed the role of PEU in affecting the satisfaction of users (Kashive et al., 2020). Once users believe they can easily and quickly master the new systems, they will more likely adopt it. Thus, when users believe that ChatGPT is easy to use, it is expected that users will express a higher satisfaction level with ChatGPT, leading them to continue using it. Thus, the hypothesis is formulated as follows:

H5: PEU positively affects satisfaction.
H6: PEU positively affects BI.

Perceived Usefulness (PU)

PU is the level at which users think that using a particular piece of technology will improve and improve their performance (Davis, 1989). PU is one of the most motivational variables in adopting and accepting IT (Basak et al., 2015). Within the context of ChatGPT, PU is related to the benefits users can gain when using ChatGPT and how it can enhance their academic performance (Niu & Mvondo, 2024).

Furthermore, when students find ChatGPT useful, it might positively affect their satisfaction, which leads to a positive intention toward using it. Thus, the hypothesis is formulated as follows:

H7: PU positively affects satisfaction.
H8: PU positively affects BI.

Confirmation

Confirmation expresses the perception of users in the level of congruence between what they expected from IS use and their performance (Bhattacherjee, 2001). Confirmation affected the perceived usefulness of a technology (Bhattacherjee, 2001). Furthermore, some studies find that confirmation is the key variable determining students' satisfaction with using IS systems (Limayem & Cheung, 2008; Stone & Baker-Eveleth, 2013; Alshammari & Alshammari R. A., 2024). When the experience of using IS systems is met and confirmed, it would more likely enhance their satisfaction level. Within the context of ChatGPT, once students' experiences with using ChatGPT is confirmed and met, they would be more likely to feel satisfied with using it. Based on that, it is hypothesized as follows:

H9: Confirmation positively affects PU.
H10: Confirmation positively affects satisfaction.

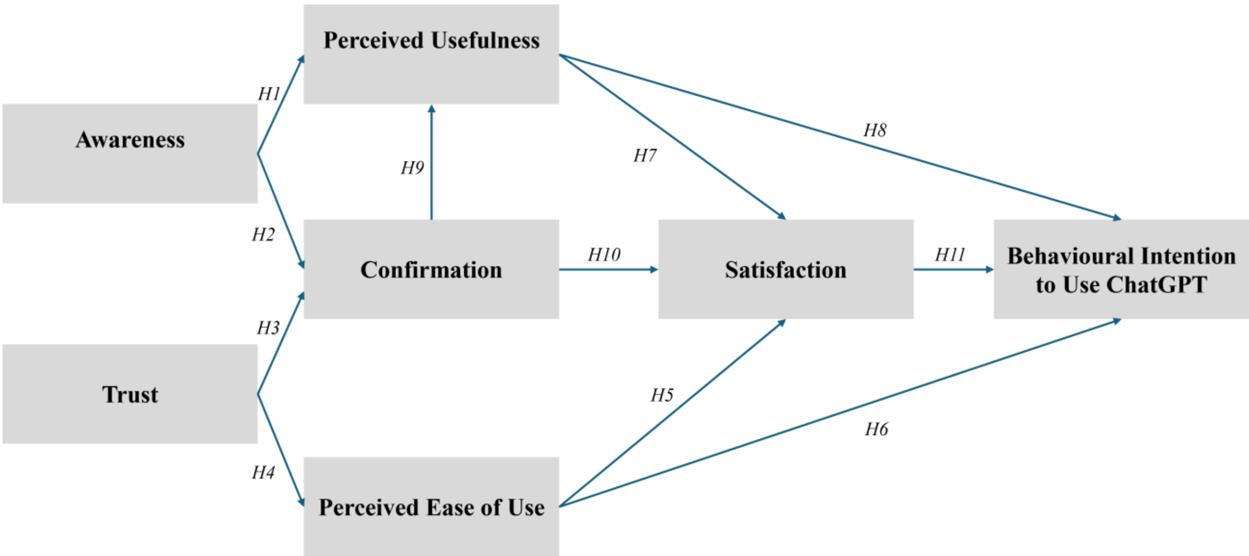
Satisfaction

Satisfaction is the user's evaluation of their experiences (Bhattacherjee, 2001), which is an essential aspect of users to have a positive intention to use and reuse a technology (Mouakket, 2015; Hong et al., 2006; Choi et al., 2019). Users with a higher satisfaction level with using specific technology tend to have a stronger intention to utilize it. Some studies have confirmed the role of satisfaction in influencing students' continuous intention toward using learning technologies in educational fields (Ifinedo, 2007; Ramadhan et al., 2022). Within the context of ChatGPT, presumably, when students are satisfied with using ChatGPT, it will affect and build positive intention toward using it. Thus, the formulated hypothesis is as follows:

H11: Satisfaction positively affects students' behavior and intention to use ChatGPT.

Figure 1 presents the research proposed model:

Figure 1
Proposed model



METHODOLOGY

Research design

The quantitative method used for this study is convenient for achieving the study's aims, which focus on assessing the relationship between constructs in the proposed model (Sekaran & Bougie, 2016).

Measurement

For this study, a questionnaire was used to collect data from students. The questionnaire has two sections: the first is concerned with demographic information, such as gender, class rank, and college, while the second is related to items that measure all constructs in the proposed model. The items that measure PEU, PU, and BI were used and adapted from Davis (1989), while items that measure awareness construct were adapted from a study by Abdalla (2024); items that measure trust were adapted from a study by Rahman et al. (2023). For ECM constructs, the items that measure confirmation were adapted from Bhattacherjee (2001), and items of satisfaction were adapted from a study Almulla (2024). A back-translation method was applied to convert the questionnaires from English to Arabic, the language of the responding students. A 5-point Likert scale for measuring items was used.

Precipitants and procedures

The questionnaire was designed using Google Forms to collect data from studies during the first semester of 2024. A sample random sampling technique was applied to collect data from respondents. All participants were from the University of Ha'il. A total of 322 students responded to the questionnaire used for further analysis.

Data Analysis

Two statistical analysis programs were used to analyze the data. SPSS was used to analyze the respondents' demographic information. A two-step in SEM AMOS, the second-generation analysis technique, was conducted to analyze the measurement and structural model. A Confirmatory Factor Analysis (CFA) was applied to assess the measurement model. Then, SEM was applied to analyze the relationships in the proposed model. SEM is a well-known multivariate analysis technique for psychological and behavior studies (Hair et al., 2010). Furthermore, Kline (2023) recommended using SEM to analyze the relationships between latent constructs.

RESULTS

A total of 322 students responded and filled out the questionnaires. Their responses proceeded to the analysis. Table 1 presents the demographic information regarding their gender and colleges. Most students were males (198, 61.5%) and females (124, 38.5%). Regarding their colleges, most students were enrolled in the College of Computer Science and Engineering (130, 40.4%), followed by the College of Arts (55, 17.1%) and the College of Business Administration (52, 16.1%), and the College of Science (36, 11.2%) and the College of Education (28, 8.7%) and the College of Medicine (15, 4.7%). In contrast, the fewest students were enrolled in the Public Health and Health Informatics College (6, 1.9%).

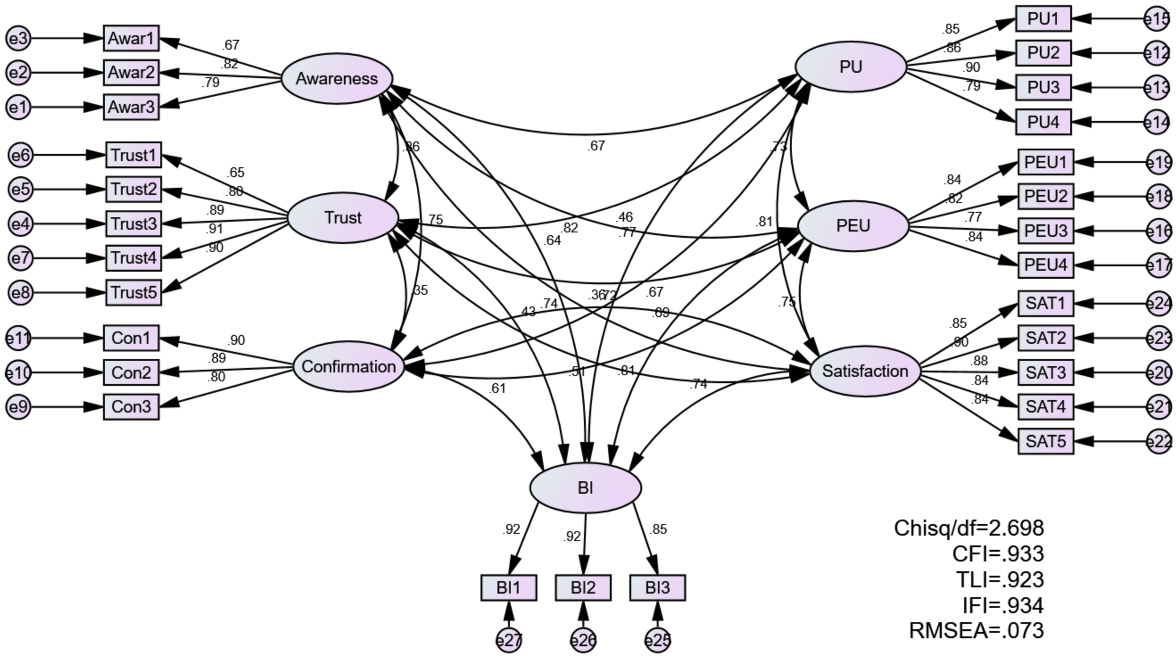
Table 1
Demographic information

		Frequency	Percent
Gender	Male	198	61.5
	Female	124	38.5
Colleges	Computer Science and Engineering	130	40.4
	Arts	55	17.1
	Business Administration	52	16.1
	Science	36	11.2
	Education	28	8.7
	Medicine	15	4.7
	Public Health and Health Informatics	6	1.9
	Total	**322**	**100.0**

Confirmatory Factor Analysis (CFA)

CFA was conducted to assess the measurement model. Construct validity is met when all indices in the model meet the suggested values recommended by prior researchers (Awang, 2015). The CFA was conducted, and its results are shown in Figure (2).

Figure 2
CFA output



The construct validity is met when all fitness indices meet the suggested values recommended by prior researchers (Awang, 2015), and the factor loading achieves the minimum suggested value of 0.6 (Yusoff et al., 2021). Table 2 shows that all fitness indexes were satisfied and exceeded prior researchers' recommended values (Hair et al., 2010; Awang, 2015). Furthermore, all factor loading of items for all constructs ranged between 0.65 and 0.92, which met the suggested satisfied value of 0.6 (Yusoff et al., 2021). Thus, construct validity is achieved.

Table 2
Fitness Indexes summary

Category	Name of Index	Index	Acceptance Value	Results
Absolute Fit	RMSEA	0.073	< 0.08	Achieved (Hair et al., 2010; Awang, 2015)
Incremental Fit	CFI	0.933	> 0.90	
	TLI	0.923	> 0.90	
	IFI	0.934	> 0.90	
Parsimonious Fit	**Chisq/df**	**2.698**	**< 3.0**	

Then, the convergent validity is met when the CR is higher than 0.70 (Rahlin et al., 2019) and the AVE is higher than 0.50 (Lowry & Gaskin, 2014). As presented in Table 3, all values of CR and AVE exceeded the suggested values. Thus, convergent validity is achieved. Furthermore, the correlation values between constructs ranged between 0.35 and 0.82, which confirms that the model has no potential multicollinearity issues that could affect the results. In addition, discriminant validity is achieved when all values in BOLD, which is the square root of AVE, are higher than other values of constructs' correlations. As shown in Table 3, the discriminant validity is satisfied and achieved the suggested values by Sarstedt et al. (2021) and Afthanorhan et al. (2021).

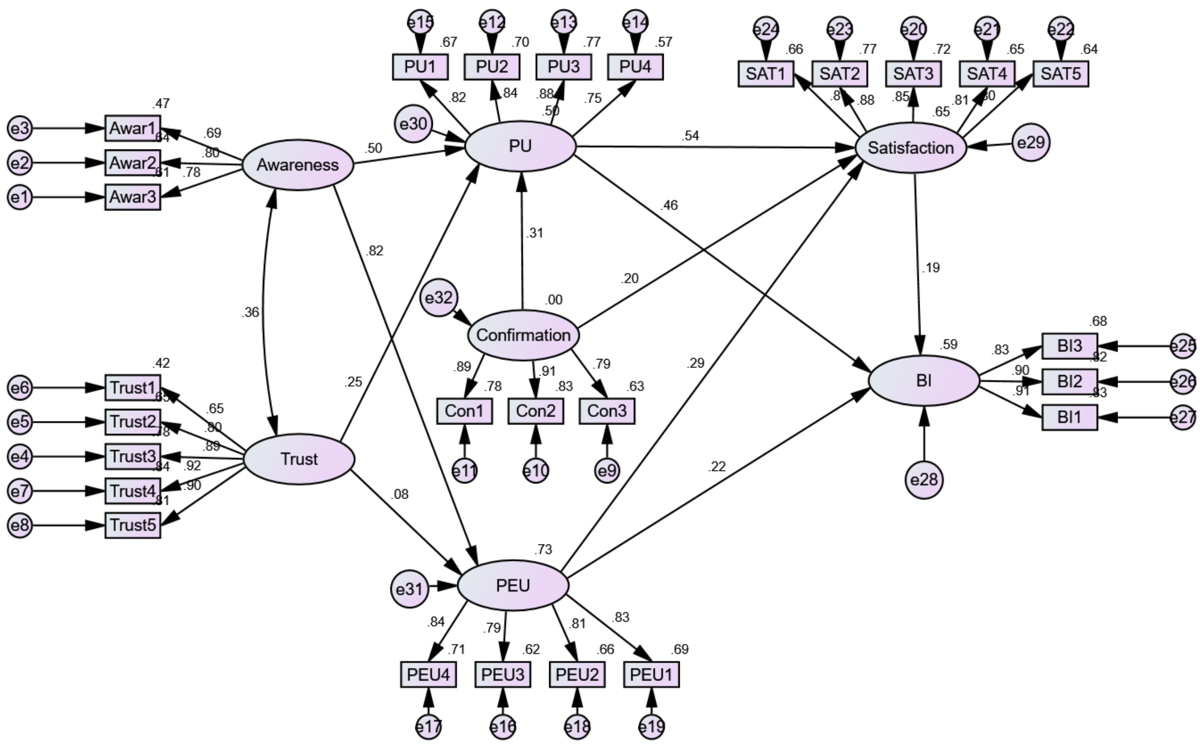
Table 3
Reliability, Convergent and Discriminant Validity

	CR	AVE	Satisfac-tion	Aware-ness	Trust	Confir-mation	PU	PEU	BI
Satisfaction	0.936	0.744	**0.863**						
Awareness	0.807	0.585	0.738	**0.865**					
Trust	0.920	0.699	0.507	0.359	**0.836**				
Confirmation	0.899	0.748	0.723	0.752	0.354	**0.865**			
PU	0.913	0.725	0.807	0.669	0.455	0.671	**0.851**		
PEU	0.891	0.672	0.752	0.824	0.362	0.805	0.732	**0.839**	
BI	0.925	0.805	0.736	0.636	0.430	0.611	0.774	0.692	**0.897**

Standardized estimate

The standardized estimate is needed to assess the R2, factor loading and coefficient beta, whereas the unstandardized estimate is essential for assessing the testing of the hypothesis. Standardized is run first, and its output is shown in Figure 3 below.

Figure 3
Standardized estimate

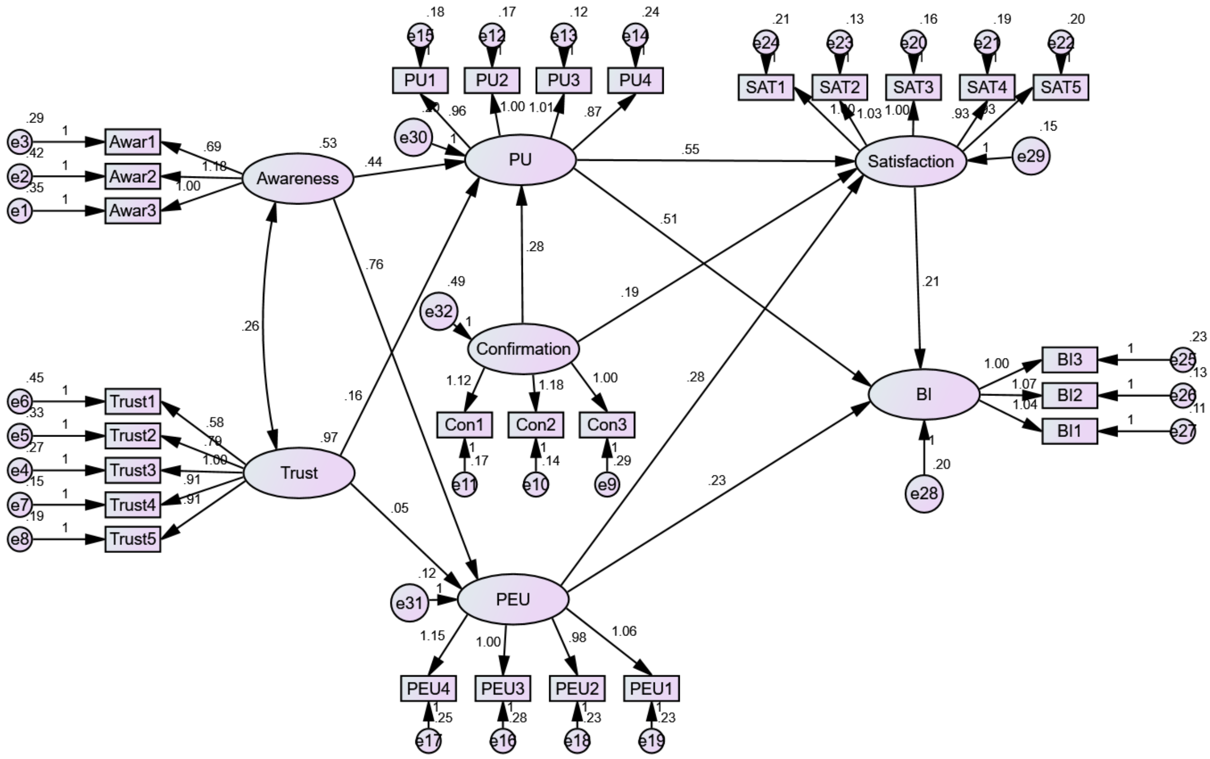


Furthermore, according to Cohen (1988), the value of R square which is above 0.26 indicates a higher explanatory power of the model. Thus, as shown in Figure 3, the R2 of the dependent variable, namely BI is 0.59, showing a high explanatory power and meaning that 59% of students' behavior intention to use ChatGPT is explained by other factors in the proposed model such as satisfaction, PU, confirmation, PEU, awareness and trust.

Unstandardized estimate

The unstandardized estimate is used to assess the regression beta and critical ratio which is essential for the hypothesis testing. The unstandardized estimate is run; its results is presented in the Figure 4 below.

Figure 4
Unstandardized estimate



Hypotheses testing results

The results confirm that Awareness had a positive significant effect on both PU and PEU "β = 0.441, p < 0.05; β = 0.765, p < 0.05"., confirming hypotheses H1 and H2. Furthermore, trust had a positive significant effect on PU "β = 0.161, p < 0.05" and an insignificant effect on PEU "β = 0.054, p > 0.05". Thus, H3 is supported, and H4 is rejected. Also, PEU positively affected satisfaction and BI "β = 0.297, p < 0.282; β = 0.232, p < 0.05," confirming Hypotheses H5 and H6. Furthermore, PU positively affected satisfaction and BI "β = 0.549, p < 0.282; β = 0. 506, p < 0.05" supporting hypothesis H8. In addition, Confirmation affected positively PU and Satisfaction "β = 0.279, p < 0.282; β = 0.188, p < 0.05" confirming the supports of H9 and H10. Finally, satisfaction significantly affected BI "$\beta = 0.209$, $p < 0.05$." Thus, H11 is supported. Table 4 presents the regression weight.

Table 4
Regression Weights

			Estimate	SE.	CR.	P	Results
PU	<---	Awareness	.441	.053	8.267	***	Significant
PEU	<---	Awareness	.765	.066	11.556	***	Significant
PU	<---	Trust	.161	.034	4.718	***	Significant
PEU	<---	Trust	.054	.032	1.664	.096	Insignificant
PU	<---	Confirmation	.279	.046	6.079	***	Significant
Satisfaction	<---	PEU	.282	.051	5.496	***	Significant
Satisfaction	<---	PU	.549	.061	9.007	***	Significant
Satisfaction	<---	Confirmation	.188	.042	4.457	***	Significant
BI.	<---	Satisfaction	.209	.083	2.510	.012	Significant
BI.	<---	PU	.506	.085	5.944	***	Significant
BI.	<---	PEU	.232	.059	3.947	***	Significant

DISCUSSION

This study integrated the extended TAM, including awareness and trust, with ECM to assess the influence on students' intention to utilize ChatGPT. Awareness had a significant positive effect on both PU and PEU. These findings align with these studies (Mutahar et al., 2018; Almuraqab, 2020; Bamigbola & Adetimirin, 2020; Abdalla, 2024). Results confirmed the important role of awareness in affection students' perceived usefulness and ease of using ChatGPT. Once students know more about ChatGPT and its assistance, they will see its usefulness in supporting their academic learning. Furthermore, once students are aware of the capabilities of ChatGPT, they will be more likely to perceive it as a useful application that supports their learning process, offering instant information, assisting in explaining complicated concepts and providing language support.

Similarly, when students have experience using ChatGPT, they would perceive ChatGPT as easy to use to support their learning. Students who are aware of the potential advantages of ChatGPT will be more willing to use this tool for their learning tasks, thereby increasing adoption level. On the contrary, little knowledge of ChatGPT could decrease PU and PEU, which could make students not know that ChatGPT has wonderful advantages and usefulness, making them see ChatGPT as too complex and complicated to apply. In addition, the findings revealed that trust significantly affected PU (Torrent-Sellens et al., 2021; Liu & Tao, 2022). Once students trust ChatGPT's reliability, accuracy, and ethical utilization of its information, they will perceive it as a useful application for their learning. This trust could encourage students to keep using ChatGPT for many learning tasks such as problem-solving, research, and assisting in writing, as that will make them believe that ChatGPT could offer excellent output. However, the findings revealed that trust had an insignificant effect on PEU. This finding might be explained that when trust in ChatGPT might affect students' perceived usefulness PU, it does not necessarily affect their judgment and perception regarding how easy or difficult ChatGPT is to use. For instance, once students perceive ChatGPT as a reliable application to provide information or assist with their learning tasks, their perceived usefulness of ChatGPT will increase. However, this trust does not necessarily make ChatGPT as easy to use for their learning.

The findings also revealed that confirmation had a significant positive effect on both PU and Satisfaction. These findings are consistent with these studies (Bhattacherjee, 2001; Stone & Baker-Eveleth, 2013; Joo & Choi, 2016). This implied that once students have more experience and become familiar with using ChatGPT, that would increase their perception of usefulness and increase their satisfaction with using ChatGPT, especially when they feel that ChatGPT can offer them services and functions that could improve their learning efficiency and performance, assisting them to achieve their learning objectives successfully and smoothly with less required efforts.

Additionally, PU and PEU had a significant effect on BI (Nja et al., 2023; Pillai et al., 2023; Chen et al., 2023). These findings explain that once students perceive ChatGPT as useful, they are more likely to build a positive intention toward using it, as ChatGPT could assist them in their learning tasks, such as saving time when doing learning tasks or improving the learning quality. Alternatively, PEU could affect BI to use ChatGPT by making ChatGPT easy to access and less complicated. Once students believe ChatGPT is easy to use, they are more likely to use it because it does not require more effort to learn how to use it. This would build a positive intention toward using it. Furthermore, the findings revealed that PU and PEU affected students' satisfaction, confirming previous studies (Kashive et al., 2020; Al-Fraihat et al., 2020; Yu et al., 2024). This finding might explain that once students perceive ChatGPT as useful, it motivates them to use it more frequently and builds a high satisfaction level for them with ChatGPT. Similarly, once students believe that using ChatGPT is easy, their satisfaction levels might increase. Furthermore, satisfaction affected students' BI when using ChatGPT, confirming previous studies (Chen et al., 2020; Yu et al., 2024). The findings might explain that once students are pleased with using ChatGPT for their learning tasks, that would build a positive intention toward using it and become more likely to use it. Satisfied students are more likely to perceive ChatGPT as worthy and beneficial, which motivates them to use it regularly with their learning tasks.

Implications

Theoretical implication

Integrating the extended TAM, with the added factors of awareness and trust, with the ECM model to assess students' behavior intention to use ChatGPT contributes to the theoretical literature on the subject. While TAM mainly focuses on PU and PEU, and ECM focuses on users' confirmation and satisfaction, including awareness and trust, it offers a more comprehensive framework model. By integrating both models with the external factors, this study offers a nuanced understanding of determinant factors that affect students' acceptance, which goes beyond the original variables of ECM and TAM. Furthermore, this study bridges the gap in the literature as awareness and trust are discussed often with technology adoption, but they are not commonly incorporated together in one single model. Thus, this study theoretically bridges this gap by demonstrating how awareness and trust could act as critical antecedents that shape students' perceptions of ChatGPT regarding PU and PEU. It offers evidence that awareness directly affects both PU and PEU. In contrast, trust only directly affects PU, highlighting the different roles these factors could play in adopting ChatGPT.

Additionally, even though TAM and ECM have been widely utilized in several studies of technology adoption, using these integrated models in AI context and ChatGPT is relatively new. Thus, this study contributes to the theoretical understanding regarding how these two integrated models could be adapted to examine the adoption of AI technologies, namely ChatGPT. This application could inspire future studies to further assess both ECM and TAM in the context of AI tools or other emerging established technologies. Furthermore, the integration of the extended TAM and ECM improved the predictive power in the model in explaining the behavior intention of using ChatGPT as the R2 value of the model is 0.59, deemed sustainable. According to Sarstedt et al. (2014), the rule of thumb regarding the R2 value is that 0.19 is weak, 0.33 is moderate, and 0.67 is deemed to be sustainable. These findings revealed that integrating the extended TAM and ECM successfully predicted the behavior intention to use ChatGPT by capturing the effect of students' prior knowledge (awareness) and their belief in the system reliability (trust) alone with other factors of TAM and ECM. Thus, combining extended TAM and ECM contributes to theoretical advancement by offering a better explanation of ChatGPT adoption than utilizing ECM or TAM individually.

Practical implication

This study has several important practical implications. Since awareness affects both PU and PEU, educators should raise awareness regarding the potential and benefits of using ChatGPT in enhancing students' learning outcomes. Awareness can be raised by integrating ChatGPT into class activities to show them the practical benefits they can gain when using ChatGPT. Educators could also offer workshops to present the huge benefits students can gain by using ChatGPT for their learning activities. Furthermore, trust influenced students' PU. Thus, educators and instructors could share research findings of using ChatGPT in education, success stories, and case studies to help build confidence in using ChatGPT for students' learning. This could lead to perceiving ChatGPT as more useful and effective for students' learning. Furthermore, since both PU and PEU influenced students' satisfaction, educators and instructors should receive feedback to continue improving how ChatGPT can be integrated and used in their courses. Offering valuable resources and ongoing support with ChatGPT leads to a better understanding and use of ChatGPT, enhancing their satisfaction.

Additionally, while PEU affects both satisfaction and BI, developers should enhance the user interface of ChatGPT to make it easier to use and intuitive, hence increasing PEU. Making features of ChatGPT simple and easy to use could increase students' satisfaction, which leads to building a positive behavior intention toward using ChatGPT. Furthermore, developers should build trust features such as showing how ChatGPT responses are generated and the reliability of the information, which could enhance students' trust. Furthermore, since awareness affects both PU and PEU, developers should provide instructors with information regarding the limitations and capabilities of ChatGPT, such as incorporating tutorials, guides, and use cases within the ChatGPT apps. This could assist students in understanding better how to use it and make it easier to use. Furthermore, policymakers could support initiatives to promote AI literacy in educational institutions to boost trust and awareness of ChatGPT. Additionally, since trust influences the PU of ChatGPT, policymakers should set guidelines for the responsible use of ChatGPT by creating ethical guidelines and policies for using ChatGPT in education, which could assist in alleviating concerns and building confidence among students. These policies could address content accuracy, data privacy, and the role of ChatGPT in learning. These implications could foster a supportive environment for the effective utilisation and adoption of AI ChatGPT in education, addressing the influential factors affecting students' behavior and intention to utilise ChatGPT.

Limitations and future work

This study has some limitations. The sample of this study is from one university, which could not be generalizable to other settings. The behavior intention to use ChatGPT could be affected differently in different disciplines, contexts, educational systems, or cultural backgrounds. In addition, a quantitative approach is used in this study. Thus, future studies could use mixed approach quantitative and qualitative methods, which could offer a deep understanding of the adoption phenomena of ChatGPT through interviews and questionnaires for gathering data. Furthermore, while this study focused mainly on awareness and trust, other factors could affect the behavior intention to use ChatGPT. Thus, future research could assess other factors which could affect the adoption of ChatGPT for students' learning, such as institutional support, prior experience with ChatGPT, and social influence.

Conclusion

This study offered valuable insight into the factors influencing students' behavior intention to use ChatGPT by an integration of the extended TAM (including awareness and trust) and the ECM model. The findings revealed that awareness is critical in shaping PU and PEU, while trust significantly affected PU, not PEU. Additionally, PU, PEU, and confirmation contributed to students' satisfaction, which positively affected students' behavior and intention to utilize ChatGPT. These results show the importance of building trust and fostering awareness of AI ChatGPT to enhance the adoption and utilization of ChatGPT among students for their learning.

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