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Factors affecting ChatGPT use in education employing TAM: A Jordanian universities' perspective

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A B S T R A C T

The widespread adoption of artificial intelligence (AI) technologies, including ChatGPT, into education, has become a focal point of attention in recent years. This research explores the connections among perceived usefulness (PU), perceived ease of use (PEOU), attitude toward using ChatGPT (ATUC), and intention to use ChatGPT (ITUC) within Jordanian universities. A survey was employed to gather information from 523 university students in Jordan, and the hypotheses were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings revealed that perceived usefulness and perceived ease of use positively impacted attitude toward using ChatGPT and intention to use ChatGPT. Attitude toward using ChatGPT positively impacted intention to use ChatGPT. Implications from this research are crucial to provide developers, instructors, and institutions in Jordan with useful information to help them successfully incorporate ChatGPT into the educational process.

1. Introduction

The extensive adoption of artificial intelligence (AI) technologies, including natural language processing (NLP) techniques and machine learning algorithms, and their incorporation into education, has gained significant attention in recent times. This increased interest is largely due to the potential of these technologies to improve both learning outcomes and student engagement. As a result, educators now have the capacity to integrate innovative teaching methods that were unavailable before. Chatbots have been explored as a tool to enhance student learning and support (Rukhiran et al., 2022). Chatbots are computer programs designed to simulate human conversation, and they have been used in various educational contexts to help, feedback, and guidance (Muniasamy & Alasiry, 2020; Yamada et al., 2016). As chatbots gain more prominence, several educational institutions have started incorporating them into their systems to facilitate and enhance the learning process (Rukhiran et al., 2022). One such technology that has gained popularity in recent years is ChatGPT, an AI-based chatbot that can simulate human-like conversations (Rukhiran et al., 2022). It is an artificial intelligence-based language model trained by OpenAI, capable of generating human-like responses to various inputs (Kirmani, 2022). As the use of ChatGPT in education is gaining momentum, it is essential to examine the factors that influence its use. ChatGPT has been employed in various educational contexts, including language learning, academic advising, and student support services (Liu et al., 2021). Despite its potential benefits, the adoption of ChatGPT in education has been slow, with many educators and students hesitant to embrace this technology (Rukhiran et al., 2022).

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The Technology Acceptance Model (TAM) has been widely used to understand and predict users' acceptance and usage behavior towards technology, especially in the context of education (Davis, 1989). Several studies have emphasized the importance of TAM in predicting the usage behavior of technology such as (Haytko & Baker, 2004; Bax & McGill, 2009; Kirana, 2017; Mathieson et al., 2001; Han & An, 2019). According to Davis et al. (1989), TAM is a useful framework to predict users' acceptance of new technology by examining their perceived usefulness and ease of use. The perceived usefulness (PU) of a technology refers to the extent to which it enhances an individual's performance or productivity, while perceived ease of use (PEOU) is the degree to which users find a technology easy to use (Venkatesh and Davis, 2000). This study will employ the TAM model and its application in predicting ChatGPT usage behavior from the perspective of marketing students. Several studies have explored the use of chatbots and their impact on student learning outcomes within the context of education. For example, Mındajao (2023) investigated the use of a chatbot to facilitate student learning in a blended learning environment. Their study revealed that the use of the chatbot improved students' learning outcomes and engagement. Similarly, Hwang and Chang (2021) explored the effective opportunities and challenges of chatbots within the educational sector. Their study found that the use of chatbots positively influenced students' motivation and engagement in the learning process, as well as supporting student learning and assessment. Chen et al. (2020) The study found that Chatbots significantly improved students' learning achievement. Moreover, marketing students tend to be early adopters of technology and are more likely to use new technologies in their learning process (Crittenden & Peterson, 2019; Vannavanit, 2019). Therefore, it is essential to understand the factors that influence the usage of ChatGPT in education from the perspective of marketing students.

This study seeks to contribute to the existing literature by exploring the factors that affect the usage behavior of ChatGPT in education, employing the TAM framework from the perspective of marketing students. The findings of this study will contribute to our understanding of the factors that influence the adoption of AI-based chatbots in education and provide insights for educators and practitioners on how to design effective ChatGPT-based educational interventions that can enhance learning outcomes. The next section of this paper will provide an overview of the literature on TAM and its application in predicting technology usage behavior.

2. Literature review

2.1. Perceived Usefulness (PU)

The technology acceptance model (TAM) is a well-established theory within the information technology (IT) research field that predicts user behavior towards technology (Davis, 1989). Perceived usefulness (PU) is not only a critical factor in the model that directly affects the user's intention to use technology (Davis, Bagozzi, & Warshaw, 1989; Bhattacherjee, 2001) but it is also known as a fundamental determinant of user acceptance of technology (Teo, 2009). Research has shown that perceived usefulness is a significant predictor of the intention to use a new technology (Benoit et al., 2009). Moreover, several studies found that perceived usefulness positively affects the intention to use technology (Agarwal & Karahanna, 2000; Venkatesh, Morris, Davis, & Davis, 2003). In the context of ChatGPT, in a study on ChatGPT adoption by university students, perceived usefulness was found to be a significant factor in the adoption of ChatGPT (Raman et al., 2023). Another study by Ching and Kwok (2022) found that PU was a crucial predictor of educators' intention to use technology-enhanced learning (TEL) tools. This suggests that PU may also predict the intention to use ChatGPT. Therefore, the following hypothesis was developed:

H_1: *Perceived usefulness (PU) predicts the attitude toward using ChatGPT.*

H_2: *Perceived usefulness (PU) predicts the intention to use ChatGPT.*

2.2. Perceived ease of use (PEU)

Perceived ease of use (PEU) is another critical factor in the TAM that impacts the user's intention to use technology (Davis, 1989). PEU refers to the degree to which the user perceives technology to be easy and free of effort. It is another fundamental determinant of user acceptance of technology (Teo, 2009). Several studies have revealed that PEU significantly influences users' attitudes and behaviors toward using technology (Venkatesh & Davis, 2000; Bhattacherjee, 2001). Additionally, Venkatesh et al., (2003) have found that perceived ease of use positively influences the intention to use technology. In the context of ChatGPT, perceived ease of use was also found to be a significant factor in the adoption of ChatGPT (Raman et al., 2023). Other studies also claimed that PEU is a significant predictor of educators' intention to use TEL tools (Ching and Kwok, 2022; Benoit et al., 2009). This suggests that PEU may also predict the intention to use ChatGPT. Moreover, studies have shown that PEU has a direct effect on perceived usefulness (Moon & Kim, 2001; Venkatesh et al., 2003) and are positively related (Li, 2009; Hasyim, 2019; Ching & David, 2022), which means that a system perceived as easy to use is also perceived as more useful (Venkatesh & Davis, 2000; Bhattacherjee, 2001). Therefore, the following hypotheses were developed:

H_3: *Perceived ease of use (PEU) predicts the attitude toward using ChatGPT.*

H_4: *Perceived ease of use (PEU) predicts the intention to use ChatGPT.*

2.3. *Attitude to use*

Attitude towards using technology is a key element that affects the user's intention to use technology (Venkatesh & Davis, 2000). Attitude refers to the user's negative or positive feelings towards technology (Fishbein & Ajzen, 1975). Benoit et al. (2009) claimed that that attitude toward using a new technology is one of the significant predictors of the intention to use it. Additionally, Ching and Kwok (2022) found that attitude towards usage (ATU) of technology is a dominant determinant of user intention to use technology. Several other studies confirmed the significant effect of attitude on the intention to use technology (Venkatesh et al., 2003; Wu & Wang, 2005). Moreover, Studies have shown that a positive attitude to use technology positively affects an individual's intention to use it (Mathieson, 1991; Venkatesh & Davis, 2000).

2.4. *Intention to use*

Intention to use refers to an individual's willingness to use a particular technology and is strongly influenced by PU and PEU (Davis, 1989). Intention to use is a significant determinant of actual usage behavior (Ajzen, 1991). According to the TAM, the user's intention to use technology is determined by the user's perceived usefulness and perceived ease of use (Davis, 1989). This means that if individuals perceive a technology as useful and easy to use, they are more likely to have a positive attitude towards using it and intend to use it. Several studies present the intention to use technology as a critical predictor of the actual use of technology (Davis et al., 1989; Venkatesh et al., 2003). Additionally, other studies mentioned that an individual's intention to use a technology significantly predicts actual usage behavior (Venkatesh & Davis, 2000; Bhattacherjee, 2001, Liaw et al., 2007; Venkatesh and Bala, 2008) found that ITU significantly predicted the mobile technology adoption within the workplace. Therefore, the following hypothesis was developed:

H$_5$: *Attitude toward using ChatGPT predicts the intention to use ChatGPT.*

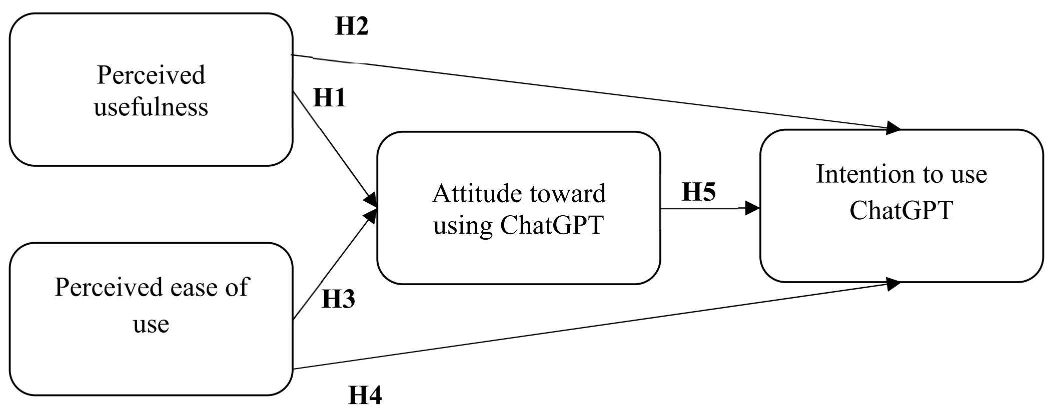

Fig. 1. The proposed model

3. Methodology

Data were collected using questionnaires from 523 students from universities in Jordan. To understand how evolving technologies are adopted, university students represent a significant demographic that is highly technologically savvy.

Table 1
Demographic characteristics

Characteristic	Frequency	Percent
Gender		
Male	166	31.7
Female	357	68.3
Age		
Under 20	115	22
20 - less than 30	277	53
30 - less than 40	90	17.2
40 -less than 50	33	6.3
50 -less than 60	6	1.1
Over 60	2	0.4
Marital status		
Single	362	69.2
Married	141	27
Divorced	16	3.1
Widowed	4	0.8

Student adoption of innovative tools and technologies makes them ideal subjects for assessing their attitudes and intentions to use ChatGPT. Their experiences with technology in educational settings provide valuable insights into how these tools are perceived and used. Their adoption of educational technologies makes them an appropriate sample for studies focusing on this topic. The items were assessed on a five-point Likert scale (1 being strongly disagree; 5 being strongly agree). Table 1 presents the demographic characteristics of the participants. Most of the participants were female (68.3%), between 20 to 30 years old (53%), and single (69.2%).

4. Analysis

Using SmartPLS 4, this study used partial least squares structural equation modeling (PLS-SEM). The PLS-SEM method was used for the following reasons. The first advantage of this method is that it improves the consistency and accuracy of the results by incorporating measurement errors (Hair et al., 2011). Additionally, it is particularly useful when dealing with models that have multiple variables (Hair et al., 2013). As a result of the simultaneous analysis of the structural and measurement models, accurate measurements can be obtained (Barclay et al., 1995).

4.1. Common method bise (CMB)

When data are gathered from a single source at the same time, common method biases can significantly influence the validity of findings (Lindell and Whitney, 2001). To address this issue, several strategies were implemented before and after data collection (Podsakoff et al., 2003). Pretests were conducted initially to clarify any unclear language. Furthermore, the study did not ask for any personal information about the participants. Afterwards, collinearity analysis was carried out. All variance inflation factors (VIFs) of the constructs were below the acceptable limit of 5 (Hair et al., 2021).

4.2. Measurement model

Table 2 and Fig. 2 show the results. An assessment of Convergent and Discriminant validity was conducted for the measurement model. AVE, loading, and composite reliability are examined for assessing convergent validity. All constructs had outer loadings exceeding 0.7 (Hair et al., 2019). The composite reliability and average variance were found to be higher than 0.7 and 0.5, respectively (Usakli & Kucukergin, 2018; Fornell & Larcker, 1981). Further, Cronbach's alpha values were higher than 0.7 (Hair et al., 2017). Based on these criteria, cognitive validity was established.

Fornell and Larcker (1981) proposed the method used in this study to assess discriminant validity. Every construct should have a square root of the Average Variance Extracted (AVE) greater than its correlation with other constructs. In Table 3, these square roots are highlighted in bold along the diagonal. Each construct's square root was higher than its correlation with each other, confirming discriminant validity.

Table 2
Measurement model

Constructs	Items	Factor loading	AVE	CA	CR	VIF
Perceived usefulness	PU1	0.793	0.690	0.850	0.899	1.724
	PU2	0.859				2.175
	PU3	0.844				2.059
	PU4	0.826				1.841
Perceived ease of use	PEOU1	0.804	0.687	0.848	0.898	1.738
	PEOU2	0.859				2.201
	PEOU3	0.829				1.928
	PEOU4	0.822				1.853
Attitude toward using ChatGPT	ATUC1	0.856	0.736	0.880	0.918	2.199
	ATUC2	0.865				2.341
	ATUC3	0.865				2.274
	ATUC4	0.846				2.100
Intention to use ChatGPT	ITUC1	0.831	0.707	0.862	0.906	1.984
	ITUC2	0.856				2.164
	ITUC3	0.846				2.024
	ITUC4	0.829				1.907

Notes: AVE: Average variance extracted; CA: Cronbach's alpha; CR: Composite reliability; VIF: Variance inflation factor

Table 3
Discriminant validity

Variables	ATUC	ITUC	PEOU	PU
ATUC	**0.858**			
ITUC	0.723	**0.841**		
PEOU	0.797	0.727	**0.829**	
PU	0.772	0.718	0.720	**0.831**

Notes: Bold and diagonal values are the square root of AVE, and off-diagonal represent correlation matrix

Lastly, we examined the overall model before moving on to the structural model. A normed fit index (NFI) and the standardized root mean square residual (SRMR) were used to evaluate the goodness of fit. The SRMR and NFI values were 0.050 and 0.894, respectively. Hu and Bentler (1999) recommend an SRMR value of less than 0.08. For the NFI value, a value closer to one indicates a better fit (Lohmoller, 1989). Hence, the model is acceptable.

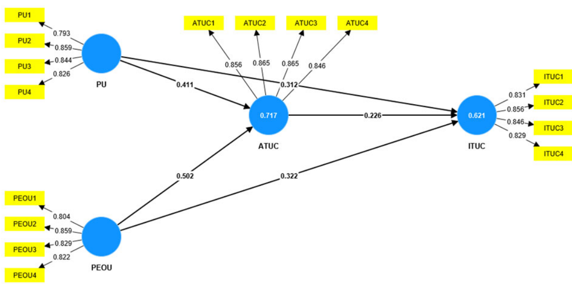

Fig. 2. Measurement Model

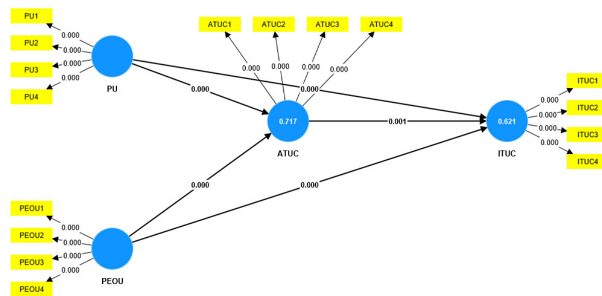

Fig. 3. Structural Model

4.3. Structural model

After confirmatory testing of the measurement model's validity and reliability and the model fit, the structural model was evaluated in terms of coefficient determination (R^2), predictive relevance (Q^2), and the path coefficient (β). The model was tested using bootstrapping (5000 samples). The results are shown in Table 4 and Fig. 3. In terms of coefficient determination, the R^2 value for attitude toward using ChatGPT is 0.717, indicating that perceived usefulness and perceived ease of use explain 71.7% of the variance in attitude toward using ChatGPT. Moreover, perceived usefulness, perceived ease of use, and attitude toward using ChatGPT explain 62.1% of the variance in intention to use ChatGPT. Based on the R^2 values, we concluded that this model had a moderate to substantial explanatory power (Hair et al., 2017). Furthermore, a Stone-Geisser blindfolding method was also used to examine predictive relevance, which showed Q^2 values exceeding zero.

Table 4
Structural model

Hypotheses	**Relationship**	**Path**	**t-value**	**p-value**	**Direction**	**Results**
Hypothesis 1	PU → ATUC	0.411	8.187	0.000	Positive	Supported
Hypothesis 2	PU → ITUC	0.312	5.259	0.000	Positive	Supported
Hypothesis 3	PEOU → ATUC	0.502	9.773	0.000	Positive	Supported
Hypothesis 4	PEOU → ITUC	0.322	5.574	0.000	Positive	Supported
Hypothesis 5	ATUC → ITUC	0.226	3.233	0.001	Positive	Supported
Coefficient determination						
$R^2_{ATUC} = 0.717$ $R^2_{ITUC} = 0.621$						
Predictive relevance						
$Q^2_{ATUC} = 0.713$ $Q^2_{ITUC} = 0.603$						

5. Discussion

Perceived usefulness has a positive and significant influence on attitude toward using ChatGPT (β = 0.411, $p < 0.001$) and on intention to use ChatGPT (β = 0.312, $p < 0.001$), confirming H1 and H2. This is consistent with Raman et al. (2023) and Ching and Kwok (2022) who found PU is a significant predictor of technology-enhanced learning tools adoption. The positive relationship between PU and both attitude and intention to use ChatGPT highlights the importance students place on ChatGPT's practical benefits in enhancing their learning experience. It is consistent with the TAM framework's emphasis on usefulness as a driving force behind technology adoption that the more students perceive ChatGPT as beneficial to their studies, the more likely they are to adopt it.

Perceived ease of use has a positive and significant influence on attitude toward using ChatGPT (β = 0.502, $p < 0.001$) and on intention to use ChatGPT (β = 0.322, $p < 0.001$), confirming H3 and H4. This finding is consistent with Venkatesh et al. (2003) and Bhattacherjee (2001), who found that PEU influences technology adoption decisions. It is evident that the more user-friendly ChatGPT is perceived, the more positively students will view and use it. ChatGPT should be student-friendly and accessible to facilitate student technology acceptance.

Moreover, attitude toward using ChatGPT has a positive and significant influence on intention to use ChatGPT ($\beta = 0.226$, $p = 0.001$), confirming H5. The findings are similar to those of Mathieson (1991) and Venkatesh & Davis (2000), who found that a positive attitude towards technology influences an individual's intention to use the technology. The study suggests students' overall sentiment towards ChatGPT, shaped by factors such as perceived usefulness and ease of use, has a significant impact on their decision to use this AI tool in their educational pursuits.

6. Research implications

There are significant theoretical and practical implications for this study. The first theoretical Implication is related to the TAM model. The positive influence of perceived usefulness and ease of use on the intention to use ChatGPT aligns with TAM and similar theoretical frameworks. This reinforces the applicability of established models in predicting technology adoption in educational contexts. The second implication is considering Attitude as a Predictor; The confirmation that attitude toward using ChatGPT significantly influences intention to use echoes the importance of individuals' subjective feelings and perceptions in the technology adoption process. The finding contributes to the ongoing discourse on the role of attitude in shaping user behavior. Moreover, the practical implications are as follows. Understanding the positive impact of perceived usefulness and ease of use implies that efforts to enhance these aspects of ChatGPT can lead to increased adoption among students. Developers and educators should focus on making the tool more practical and user-friendly to maximize its utility in educational settings. The practical implication of the positive influence of perceived ease of use underscores the importance of designing intuitive and accessible interfaces for ChatGPT. Ensuring a user-friendly experience can potentially overcome barriers to adoption and encourage more students to utilize the technology. Recognizing the influence of attitude on intention to use ChatGPT suggests that efforts should be directed towards fostering positive perceptions among students. This could involve highlighting the tool's benefits, providing training, and addressing any concerns to create a favorable attitude toward integrating ChatGPT into educational practices. The findings contribute practically to educational institutions by guiding the development of strategies for incorporating AI tools like ChatGPT. Institutions can tailor their approaches by emphasizing the practical benefits and ensuring that the technology is user-friendly, ultimately fostering a positive environment for adoption. The theoretical implications reinforce existing models, while the practical implications offer actionable insights for developers, educators, and institutions in Jordan who are aiming to integrate ChatGPT into the education process successfully. By aligning with theoretical frameworks and addressing practical considerations, the effective implementation of ChatGPT in educational settings can be optimized.

7. Conclusion

The findings of this research shed light on the crucial factors influencing the adoption of ChatGPT in educational settings. The positive and significant influence of perceived usefulness (PU) on both attitude and intention to use ChatGPT aligns with prior research and underscores the importance students attribute to the practical benefits of this technology in enhancing their learning experiences. This consistency with the Technology Acceptance Model (TAM) framework emphasizes the pivotal role of perceived usefulness as a driving force behind technology adoption. Similarly, the positive impact of perceived ease of use (PEU) on attitude and intention to use ChatGPT emphasizes the significance of user-friendly interfaces in promoting favorable perceptions and encouraging usage. As suggested by prior studies, ensuring ChatGPT is perceived as accessible and student-friendly is crucial for facilitating its acceptance among students. Furthermore, the study highlights the substantial influence of attitude to use ChatGPT on intention to use, reinforcing the idea that students' overall sentiment towards the technology, shaped by factors like perceived usefulness and ease of use, significantly impacts their decision to incorporate ChatGPT into their educational pursuits. These findings provide valuable insights for educational institutions and developers to enhance the adoption of ChatGPT by prioritizing features that enhance perceived usefulness, ensuring user-friendly interfaces, and cultivating positive attitudes among students.

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