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Investigating Factors Influencing EFL Learners' Behavioral Intentions to Adopt ChatGPT for Language Learning

Noha Almansour
College of Languages and Translation, Imam Mohammad Ibn Saud Islamic University, Riyadh, Saudi Arabia

***Abstract*—This study explores factors that influence English as a foreign language (EFL) learners' behavioral intention to adopt ChatGPT for language learning. To explore this topic, a research model based on the technology acceptance model (TAM) was proposed and used to evaluate hypotheses on the relationship between model constructs. The proposed model includes the constructs perceived usefulness (PU), perceived ease of use (PEoU), behavioral intentions, and computer self-efficacy. In addition, the study examines the effect of the moderating variables, gender and education level, on the relationships between the proposed model constructs. Structural equation modeling (SEM) was applied to the data of 211 EFL learners to analyze causal relationships between the model constructs and the effect of the moderating variables. Findings indicated that EFL learners' behavioral intentions to adopt ChatGPT for language learning were greatly impacted by their PU. In addition, computer self-efficacy was a powerful determinant influencing learners' PEoU and PU. Furthermore, education level had no significant moderating effect on learners' perceptions or intentions to adopt ChatGPT. However, gender only moderated the relationship between computer self-efficacy and PEoU, with the relationship being stronger for women. All the proposed hypotheses on the relationships between the model constructs were supported; therefore, this study contributed to the validation of TAM for predicting learners' acceptance and adoption of ChatGPT for language learning.**

***Index Terms*—technology acceptance model, ChatGPT, artificial intelligence**

I. Introduction

Recent years have brought rapid progress in technology, especially in the field of artificial intelligence (AI). These developments have significantly impacted education. Several generative AI tools have been used for educational purposes, and one of these tools is the chatbot. Zumstein and Hundermark (2017) defined a chatbot as a computer program that utilizes a text-based dialogue system to imitate human language. Chatbots have emerged following advancements in natural language processing (NLP) and machine learning (Adamopoulou & Moussiades, 2020). In language learning, chat-based tools have received attention due to their ability to engage in natural conversations with learners and their valuable pedagogical applications (Huang et al., 2022). Five pedagogical uses of chatbots in language learning have been identified: interactive interlocution, simulation, content transmission, learner support, and resource recommendation (Huang et al., 2022).

An increasingly popular chatbot that has recently attracted significant attention is the Chat Generative Pre-Trained Transformer (ChatGPT). ChatGPT relies on a large language model (LLM) that leverages a vast amount of data and generates human-like text on a wide range of topics (Van Dis et al., 2023). The release of ChatGPT in November 2022 sparked discussions and debates about the potential benefits, limitations, and ethical considerations of using language models in different contexts (Van Dis et al., 2023). These controversial debates have positioned ChatGPT as "the most high-profile and controversial form of AI to hit education so far" (Williamson et al., 2023, p. 2).

The integration of ChatGPT in education for English language learning represents an innovative and revolutionary approach that has the potential to bring about a significant shift in the field by enabling personalized, interactive learning; automated rating; and real-time feedback (Javaid et al., 2023). The incredible benefits offered by ChatGPT have convinced many researchers that investigating students' perspectives on its acceptability is essential for embracing this emerging technology in education. Students' acceptance or rejection of ChatGPT can significantly influence its integration into educational settings. Therefore, understanding learners' behavioral intentions to adopt ChatGPT is essential for helping educators, practitioners, and instructors make decisions regarding the use of this emerging technology in educational settings. However, the implementation of ChatGPT in education presents some challenges, including ethical issues, insufficient evaluation, user attitudes, data integration issues, plagiarism, and language proficiency challenges (Kooli, 2023).

Although many studies have examined the benefits and drawbacks of adopting ChatGPT in education, there is a limited body of research specifically focused on learners' adoption of ChatGPT in language learning settings. This study addresses this gap in the literature and contributes to expanding knowledge on Saudi EFL learners' perceptions and intentions to adopt ChatGPT for learning English in higher education. Additionally, this study validates the use of the technology acceptance model (TAM) in predicting language learners' adoption of ChatGPT. To achieve these aims, this study investigated factors affecting Saudi EFL learners' behavioral intentions to adopt ChatGPT for language learning in higher education using the TAM framework. Moreover, the study examined the effect of the moderating variables gender and education level on learners' behavioral intentions to adopt ChatGPT for language learning.

II. Theoretical Framework and Hypotheses Development

A. TAM as a Conceptual Framework

For over two decades, user technology acceptance has been a significant area of research, providing insights into the successful adoption of technological innovations (Davis, 1989). Several models of technology acceptance offer a suitable framework for researchers to explore users' acceptance of new technologies. One of the most popular models is TAM, as proposed by Davis (1989). Since its introduction in 1989, TAM has gained significant attention and has been extensively used and tested by numerous researchers (Venkatesh & Davis, 1996; Venkatesh & Davis, 2000).

Many factors can influence users' acceptance of a technology (Davis, 1989). TAM provides a theoretical framework for understanding and predicting users' adoption and acceptance of new technologies. The original framework of TAM highlighted four key constructs: perceived ease of use (PEoU), perceived usefulness (PU), attitude, and behavioral intentions (Davis, 1989). According to Davis (1989), PU refers to users' perceptions of a particular technology in terms of its productivity potential, effectiveness, and efficiency in accomplishing specific tasks. PEoU, on the other hand, relates to users' perceptions regarding the effort involved in using a particular technology. Behavioral intention describes users' decisions to engage in actions related to the use of a particular technology (Davis, 1989). Finally, attitude toward use describes an individual's attitude towards using a specific technology and is considered a mediating variable in the original TAM (Davis, 1989).

A modified model proposed by Venkatesh and Davis (1996) excluded the construct attitude and included external variables as factors influencing the perception of ease and usefulness. Additionally, some studies have excluded the attitude construct from their model because it partially mediates the relationship between PEoU and PU towards behavioral intentions (Davis & Venkatesh, 1996; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008). Therefore, this study excluded the attitude construct from TAM and focused primarily on PEoU, PU, and computer self-efficacy in relation to learners' behavioral intentions to adopt ChatGPT.

In the technology acceptance literature, several studies have confirmed that individuals' behavioral intentions are influenced by their perceptions of ease of use and usefulness of a technology and that behavioral intentions can predict actual use (Davis & Venkatesh, 1996; Davis, 1989; Venkatesh & Davis, 2000; Davis et al., 1989). Chin and Todd (1995) stated that the likelihood of adopting a particular technology is strongly determined by the associated perceptions of its usefulness or ease of use. Many studies reported in the literature have revealed that PEoU has a strong direct effect on PU (Venkatesh & Davis, 1996; Agarwal & Prasad, 1999). In the original model of TAM, both PU and PEoU predict individuals' attitudes towards a particular technology, and PEoU can predict users' intentions to use this technology through the mediating variable of PU (Davis, 1989).

Research on technology acceptance in education and language learning has revealed that teachers' PEoU and PU were the most influential factors determining their use of technology in the classroom (Teo et al., 2018). Similarly, Mou et al. (2022) found that learners' PU and PEoU greatly influenced their behavioral intentions to adopt a digital platform for learning purposes. Based on TAM and previous studies, the following hypotheses are proposed in the present study:

H1: PEoU positively affects PU.

H2: PU positively affects behavioral intentions.

H3: PEoU positively affects behavioral intentions.

Several studies reported in literature have added different external variables to TAM. Commonly added variables include computer self-efficacy, computer anxiety, computer playfulness, and computer experience. For this study, only computer self-efficacy was added as an external variable to the proposed model.

B. Computer Self-Efficacy and TAM

The concept of self-efficacy, defined as individuals' beliefs about their own capabilities to perform a specific task (Bandura, 1977), is considered an important element in social cognitive theory and has significant implications in the field of technology acceptance. Compeau and Higgins (1995) used the term computer self-efficacy to describe individuals' beliefs about their own capabilities to complete certain tasks. Venkatesh and Davis (1996) found that computer self-efficacy influenced users' PEoU. Several studies have reported that computer self-efficacy plays a significant role in influencing individuals' behavioural intentions to use a new technology and that it is mediated by two important variables: PEoU and PU (Venkatesh & Davis, 1996; Terzis & Economides, 2011). Terzis and Economides (2011) indicated that computer self-efficacy influenced behavioral intentions indirectly through its impact on other intermediate factors, such as attitudes, PU, and PEoU. They also revealed that computer self-efficacy had a direct impact on PEoU.

Based on the reviewed studies, the following hypotheses were proposed:

H4: Computer self-efficacy positively affects PU.

H5: Computer self-efficacy positively affects PEoU.

H6: Computer self-efficacy positively affects behavioral intentions.

C. TAM And Gender

Studies investigating the effect of gender as a moderating factor on TAM constructs have yielded inconsistent findings. A study conducted by Venkatesh and Morris (2000) demonstrated that gender has an insignificant moderating effect on the relationship between PEoU and PU, but it has a significant moderating effect on the impact of PEoU and PU on behavioral intentions. On the other hand, Ong and Lai (2006) found that gender moderates the relationship between the two constructs, PEoU and PU, with a stronger effect for women. Based on the previous research, the following hypotheses were proposed:

H7a: Gender moderates the relationship between PEoU and behavioral intentions.
H7b: Gender moderates the relationship between PU and behavioral intentions.
H7c: Gender moderates the relationship between computer self-efficacy and PU.
H7d: Gender moderates the relationship between computer self-efficacy and PEoU.
H7e: Gender moderates the relationship between PU and PEoU.

D. TAM and Education Level

Several studies have investigated the role of education level as (i) a moderating variable on the relationship between users' perceptions and attitudes towards behavioral intention and (ii) as an antecedent variable influencing users' PU and PEoU (Agarwal & Prasad, 1999; Burton-Jones & Hubona, 2006). Findings have suggested that education level has a significant impact on the relationship between individuals' PU and PEoU and behavioral intention to adopt a particular technology (Agarwal & Prasad, 1999; Burton-Jones & Hubona, 2006). Burton-Jones and Hubona (2006) found that education level moderates PU. However, Agarwal and Prasad (1999) revealed that there was no significant relationship between educational level and PU. They added that education level was significantly related to PEoU. Based on the previous research, the following hypotheses were proposed:

H8a: Education level moderates the relationship between PEoU and behavioral intentions.
H8b: Education level moderates the relationship between PU and behavioral intentions.
H8c: Education level moderates the relationship between computer self-efficacy and PU.
H8d: Education level moderates the relationship between computer self-efficacy and PEoU.
H8e: Education level moderates the relationship between PU and PEoU.

E. Research Proposed Model

To understand the adoption of ChatGPT by EFL students, a conceptual framework based on TAM and hypotheses was proposed (see Fig. 1). Six hypotheses on the relationship between the model constructs and 10 hypotheses on the moderating effect of two moderating variables were tested. The model consists of three constructs from TAM: PEoU, PU, and behavioral intentions and one external variable, computer self-efficacy. The study excluded the construct of attitude from the proposed model based on Davis' (1989) findings that a model relying on only three constructs, namely, behavioral intentions, PU, and PEoU, is considered valuable for predicting users' intention to adopt a particular technology. Thus, the proposed model integrated three different categories of variables, including three independent variables, a dependent variable, and two moderating variables.

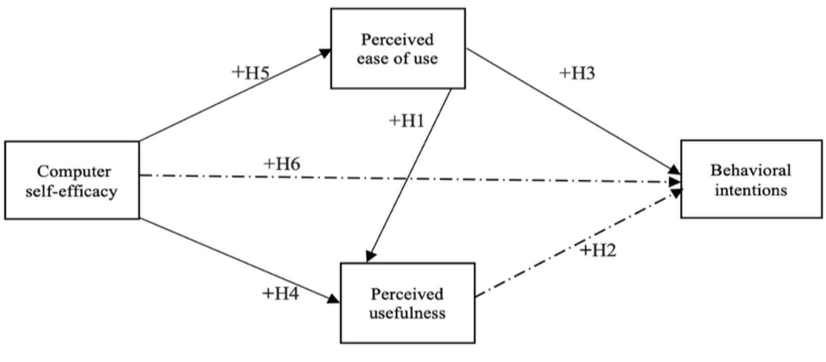

Figure 1. The Research Model

III. METHODOLOGY

A. Participants

The study utilized a cross-sectional design, employing a self-reported questionnaire administered at a single timepoint to undergraduate and postgraduate male and female EFL students enrolled in English language departments at three Saudi universities. The sample consisted of 211 EFL students, divided into four subgroups: 72 female undergraduates, 42 female postgraduates, 70 male undergraduates, and 27 male postgraduates (see Table 1). The sample average age ranged from 18 to 24 years. All participants reported being familiar with using ChatGPT, as determined by their responses to the familiarity question in the questionnaire. Students were informed that their participation was entirely voluntary, and it took approximately 20 minutes to complete the self-reported questionnaire. The questionnaire was designed to exclude any respondents who were not familiar with ChatGPT. The first question thus was, "Are you familiar with ChatGPT?" If the respondent selected "No", it would lead them to the end of the questionnaire. If the answer was "Yes", the respondent was allowed to answer the self-reported questionnaire.

TABLE 1
DEMOGRAPHIC BACKGROUND OF THE STUDY PARTICIPANTS

Category		Participant	Percentage
Gender	Male	97	45.97%
	Female	114	54.03%
Education level	Postgraduate	69	32.70%
	Undergraduate	142	67.30%
Total	211		

B. Instruments

The study utilized a self-reported questionnaire with three parts. The first collected demographic information from the participating learners, including their age, gender, education level, and familiarity with ChatGPT. The second part assessed learners' perceptions of and intentions to use ChatGPT, based on Davis' (1989) theoretical framework TAM and adapted from Belda-Medina and Calvo-Ferrer's (2022) work. This part of the questionnaire involved three constructs with 15 items: PEoU (five items), PU (eight items), and behavioral intentions (two items). A 5-point Likert scale was used to measure learners' perceptions and intentions. The third part consisted of 10 items, measured on a 7-point Likert scale, to assess learners' computer self-efficacy. This part was adopted from Holden and Rada (2011) based on Compeau and Higgins' (1995) scale. Holden and Rada (2011) updated the original scale and used a 7-point Likert scale instead of a 10-point scale.

C. Data Analysis

Structural equation modeling (SEM) was applied to examine the measurements and structural model. Prior to performing SEM, the Kaiser-Meyer-Olkin (KMO) measure was computed to assess the appropriateness of the gathered data for conducting the analysis using the Statistical Package for Social Science (SPSS; version 28). The results indicated that the KMO value (0.93; $p < .001$) was suitable for running SEM. Furthermore, normality was tested to confirm that the gathered data were normally distributed with appropriate skewness and kurtosis values.

IV. RESULTS

A. Measurement Model Assessment

In the measurement model assessment, convergent validity and discriminant validity were assessed. The convergent validity was evaluated using three tests (Fornell & Lacker, 1981). Firstly, the reliability of items was tested by examining the factor loadings to verify that each individual item loaded into its corresponding construct group with an adequate value above 0.5 (Hair et al., 2006). Table 2 displays item factor loading, which ranged from 0.71 to 0.92 and exceeded the suggested acceptable value. Secondly, the composite reliability of the constructed items was above the minimum acceptance value of 0.7 (it ranged from 0.70 to 0.97). Thirdly, the average variance extracted (AVE) was assessed, and the results indicated appropriate values. Table 3 indicates that the convergent validity was satisfactory, as all constructs met the recommended values of AVE > 0.50 and CR > 0.70 (Fornell & Lacker, 1981). Furthermore, the internal consistency of items was evaluated using Cronbach's alpha test. The results demonstrated that the reliability of the constructs, which ranged from 0.82 to 0.96, exceeded the desired value of 0.70.

TABLE 2
FACTOR LOADINGS OF TAM CONSTRUCTS

Item	Factor loading			
PEoU1	0.800			
PEoU2	0.834			
PEoU3	0.849			
PEoU4	0.796			
PEoU5	0.794			
PU1		0.710		
PU2		0.816		
PU3		0.832		
PU4		0.797		
PU5		0.819		
PU6		0.802		
PU7		0.830		
PU8		0.823		
BI1			0.929	
BI2			0.912	
CSE1				0.842
CSE2				0.844
CSE3				0.857
CSE4				0.874
CSE5				0.874
CSE6				0.904
CSE7				0.923
CSE8				0.897
CSE9				0.885
CSE10				0.894

*Behavioral intentions (BI); computer self-efficacy (CSE)

TABLE 3
AVERAGE VARIANCE EXTRACTED (AVE), COMPOSITE RELIABILITY (CR), AND CRONBACH'S ALPHA

Construct	AVE	Cr (rho-c)	Cronbach's alpha
PEoU	0.664	.908	.873
PU	0.647	.936	.922
BI	0.847	.917	.820
CSE	0.774	.972	.968

The discriminant validity was evaluated based on the Fornell-Larcker criterion. The results revealed that the AVE value for each construct exceeds the squared correlations with other constructs (see Table 4) (Fornell & Larcker, 1981). Thus, discriminant validity was satisfactory for all constructs.

TABLE 4
DISCRIMINANT VALIDITY (FORNELL-LARCKERS CRITERION)

	BI	PEoU	PU	CSE
BI	**0.921**			
PEoU	0.227	**0.815**		
PU	0.434	0.534	**0.804**	
CSE	0.507	0.345	0.649	**0.880**

** Square root of AVE is on bold*

The model fit was assessed using two informative indices: SRMR and NFI. The results of the estimated model indicated that the SRMR value was 0.08 and the NRI value was 0.80 (see Table 5). According to Hair et al. (2014), the results suggest that the model provides a good fit of the SEM and satisfies all criteria.

TABLE 5
MODEL FIT INDICES

Indices	Saturated model	Estimated model
NFI	0.80	0.80
SRMR	0.07	0.08

B. Structural Model Assessment

The structural model was assessed using Smart Partial Least Squares (SmartPLS) software to conduct SEM analysis. In SEM analysis, two informative indicators were used to predict the accuracy of the proposed relationships: the estimated standardized path coefficients (β) and the squared multiple correlations (R2).

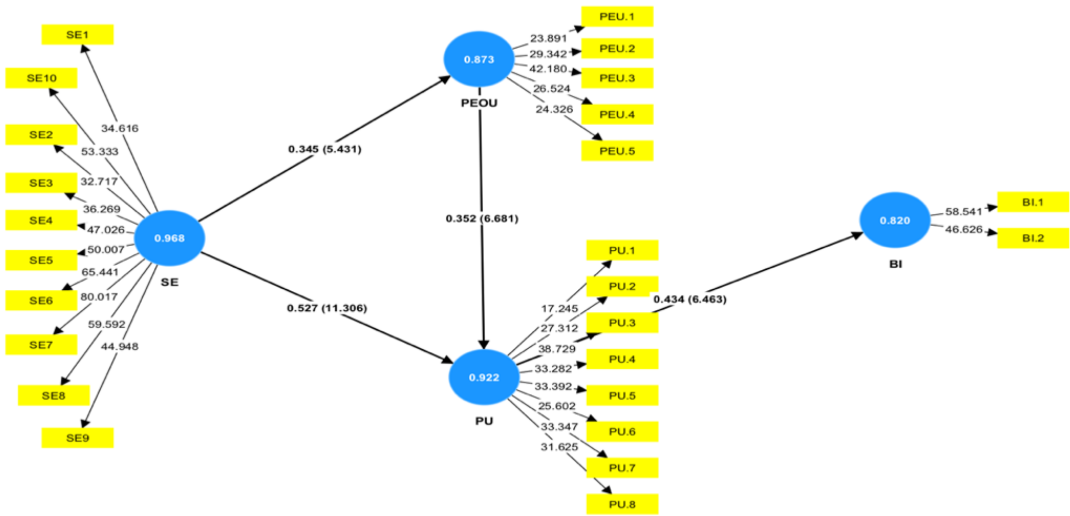

Figure 2. The Structural Model

C. Main Effects and Hypotheses Testing

The structural model employed the bootstrap resampling technique in SmartPLS to enhance the reliability of the results. The study examined hypotheses concerning direct and indirect effects on learners' intentions to adopt ChatGPT using path analysis. This analysis involved standardized path coefficients and associated *t*-values (see Figure 2). The *t*-value served as a criterion for accepting or rejecting a hypothesis, with acceptance criteria being a *t*-value above or equal to the range (-1.65 to 1.65) and a significant *p*-value ($p > 0.05$). Table 6 indicates that all the proposed hypotheses were supported with a significant *t*-value ranging from 5.436 to 11.319. The data revealed significant findings. First, PU was the strongest determinant, positively impacting learners' behavioral intentions to adopt ChatGPT ($\beta = 0.433$). Second, computer self-efficacy had a significant effect on both PU and PEoU ($\beta = 0.526$ and $\beta = 0.345$, respectively), and the strongest relationship existed between the two constructs computer self-efficacy and PU ($\beta = 0.526$). Third, PEoU has a significant effect on learners' PU of ChatGPT ($\beta = 0.352$).

TABLE 6
HYPOTHESIS TESTING OF MAIN EFFECTS USING PATH COEFFICIENT ANALYSIS

Path coefficient	β	Mean	Sd	T value	P value	Result
PEoU->PU	0.352	0.351	0.053	6.681	0.000	Supported
PU->BI	0.433	0.438	0.074	5.829	0.000	Supported
CSE->PEoU	0.345	0.349	0.063	5.436	0.000	Supported
CSE->PU	0.526	0.529	0.046	11.319	0.000	Supported

D. Mediating Effects and Hypotheses Testing

To test the indirect effects of one variable on another, a standardized path coefficient analysis is used (see Table 7). Results indicated that PEoU had a positive, indirect effect on learners' behavioral intentions ($ß = 0.153$; $p > 0.001$); this relationship was mediated by their PU towards ChatGPT. Moreover, learners' computer self-efficacy indirectly influenced their behavioral intention to use ChatGPT ($ß = 0.282$; $p > 0.001$); this result was mediated by their PU and PEoU.

TABLE 7
HYPOTHESIS TESTING OF INDIRECT EFFECTS USING PATH COEFFICIENT ANALYSIS

Path coefficient	β	Mean	Sd	T value	P value	Result
PEoU->BI	0.153	0.154	0.032	4.703	.000	Supported
CSE->BI	0.282	0.289	0.053	5.288	.000	Supported

E. Moderating Effects and Hypotheses Testing

This study employed a multi-group analysis to investigate the existence of moderating variables. In this analysis, the data were divided into two groups based on a specific grouping variable. Table 8 illustrates the path strength between the model constructs and the effect of moderators. Education level was found to be an insignificant moderator for the relationship between the research model variables. All hypotheses related to the role of education level as a moderator were rejected. Furthermore, Table 9 reveals that gender only moderated the effect of computer self-efficacy on PEoU ($ß = 0.162$; $p > 0.001$). Female learners' computer self-efficacy had a positive influence on their PEoU; however, computer self-efficacy had no positive effect on male learners' PEoU.

TABLE 8
MULTI-GROUP ANALYSIS OF THE MODERATING ROLE OF EDUCATION LEVEL

Path	Postgraduate (N=69)			Undergraduate (N=142)			ß Differences	Result
	ß	t value	p value	ß	t value	p value		
PEoU -> BI	0.02	0.178	0.859	-0.002	0.019	0.985	0.018	Rejected
PEoU -> PU	0.219	2.021	0.044	0.349	5.538	.000	0.130	Rejected
PU -> BI	0.398	3.971	.000	0.429	4.816	.000	0.031	Rejected
CSE -> PEoU	0.427	3.643	.000	0.248	2.947	0.003	0.179	Rejected
CSE -> PU	0.569	6.125	.000	0.514	9.43	.000	0.055	Rejected

TABLE 9
MULTI-GROUP ANALYSIS OF THE MODERATING ROLE OF GENDER

Path	Male (N=97)			Female (N=114)			ß Differences	Result
	ß value	t value	p value	ß value	t value	p value		
PEoU -> BI	-0.143	1.224	0.222	0.126	1.232	0.218	-0.017	Rejected
PEoU -> PU	0.337	4.753	.000	0.408	5.345	.000	0.071	Rejected
PU -> BI	0.382	3.63	.000	0.445	4.674	.000	0.063	Rejected
CSE -> PEoU	0.162	1.561	0.119	0.534	8.539	.000	0.372	Supported
CSE -> PU	0.536	7.535	.000	0.484	7.207	.000	0.052	Rejected

V. DISCUSSION AND CONCLUSION

A. Summary Key Findings

The main purpose of the study was to investigate factors influencing EFL learners' behavioral intention to adopt ChatGPT for language learning and how such factors are moderated by gender and education level. Using SEM, this study tested the proposed hypotheses on the relationship between PU, PEoU, computer self-efficacy, and behavioral intention and evaluated the moderating effects of gender and education level on learners' behavioral intentions to adopt ChatGPT. The results can be summarized as follows: first, all six hypotheses on the relationship between the model constructs were supported with a *t*-value ranging from (5.436) to (11.319). This result validated the use of the TAM framework for ChatGPT and its capability to predict EFL learners' behavioral intention to adopt ChatGPT for language learning purposes. Second, the results of the hypothesis testing revealed several significant findings. The strongest determinant of learners' behavioral intention to adopt ChatGPT for language learning was their PU (ß = 0.433; $p > 0.001$) supporting previous findings (Davis, 1989). Results revealed that PEoU and computer self-efficacy had a significant, positive, indirect effect on learner's behavioral intentions that was mediated by the variable PU (ß = 0.153, $p > 0.001$, ß = 0.282, $p > 0.001$, respectively). This finding aligns with those of previous studies (Venkatesh & Davis, 1996; Terzis & Economides, 2011). Moreover, data revealed that computer self-efficacy had a positive direct effect on learners' PU (ß = 0.526, $p > 0.001$) and PEoU (ß = 0.345, $p > 0.001$) of ChatGPT. Finally, the study found that the moderator variables gender and level of education had no significant effects on the model constructs except for the relationship between computer self-efficacy and PEoU, which appeared to be moderated by gender. These findings contrast previous studies (Agarwal & Prasad, 1999; Burton-Jones & Hubona, 2006; Venkatesh & Morris, 2000; Ong & Lai, 2006) that confirmed the role of moderating variables such as level of education and gender on the relationship between TAM constructs and behavioral intentions.

B. Implications

Understanding EFL learners' reactions towards ChatGPT in language learning is an important, yet understudied, issue. To fill the gap in the literature, this study provides an empirical analysis to help explain variables influencing EFL learners' acceptance of ChatGPT in language learning and presents a framework for future research on EFL learners' adoption of ChatGPT.

The results have several theoretical and practical implications. The results of the study contribute to the validation and applicability of the TAM model in the field of AI chatbots. The study's validation of the TAM model strengthens the theoretical foundation of the model and its applicability in the context of AI chatbots. Moreover, the study provides theoretical implications by advancing our understanding of user acceptance in relation to different factors, including PU, PEoU, and behavioral intentions, and the role of moderating factors in the adoption of ChatGPT. These implications can provide useful recommendations for policymakers, educational researchers, and faculty members to enhance user's experiences and promote widespread acceptance of ChatGPT as a sustainable tool of language learning by, for example, motivating training sessions to ensure that students are capable of effectively using these tools.

C. Limitations and Suggestions

There are several limitations to this study that future studies can address. Firstly, the study focused only on factors influencing learners' behavioral intentions to adopt ChatGPT. Further research is needed to investigate learners' actual use of ChatGPT. Second, the study adopted a cross-sectional method to investigate learners' adoption of ChatGPT, but a longitudinal study may be useful to better understand learners' acceptance and perceptions of integrating this technology into language learning after a longer period of use. Finally, further future research could investigate teachers' perceptions towards ChatGPT integration in EFL classrooms in terms of language skills development, interactions, and ethical considerations.

D. Conclusion

This study explored factors influencing EFL learners' behavioral intentions to adopt ChatGPT for language learning. It also examined the role of individual differences, gender and education level, as moderating variables influencing learners' adoption of ChatGPT. The results provide a new perspective on how ChatGPT is being adopted by Saudi EFL learners. The study concluded that the strongest determinant that affects learners' intention to adopt ChatGPT is their PU. Learners who consider ChatGPT useful are more likely to adopt it. Further, learners with high levels of computer self-efficacy were more likely to consider ChatGPT useful and easy to adopt. The study confirmed that individual variables, gender and education level, had no significant moderating effect on learners' intentions to adopt ChatGPT except for the relationship between learners' computer self-efficacy and PEoU, which was higher for female participants. The study results will empower educators, practitioners, and researchers to develop effective interventions that facilitate the integration of ChatGPT to enhance the language learning experience.

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Noha Almansour is an Assistant Professor of Applied Linguistics at the Department of English Language and Literature, College of Languages and Translation, Imam Mohammad Ibn Saud Islamic University. She has been teaching different courses in linguistics and language skills. She is interested in the areas of second/foreign language teaching and learning, pragmatic development, e-learning, and teacher cognition.