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Adopting ChatGPT: Pioneering a new era in learning platforms

Kevin Ayoubi[a*]

[a]*Higher Colleges of Technology-CERT, United Arab Emirates*

C H R O N I C L E

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A B S T R A C T

The advent of technology has dramatically reshaped the ways in which we assimilate knowledge, teach, and access information. From online learning platforms to interactive educational games and virtual reality simulations, technology has transformed the traditional classroom into a vibrant, engaging, and inclusive educational landscape. A notable advancement in artificial intelligence technology is ChatGPT (Generative Pre-trained Transformer), which provides personalized and effective learning experiences by delivering customized feedback and explanations to students. Despite the considerable research on the adoption or acceptance of e-learning, there is a paucity of research on the acceptance and utilization of ChatGPT, highlighting the need for further investigation. This study aims to bridge this gap by proposing an integrated model that incorporates three key constructs: perceived learning value, perceived satisfaction, and personal innovativeness. A questionnaire survey was administered to 289 university students in the United Arab Emirates (UAE), and the data collected were analyzed using the partial least squares-structural equation modeling (PLS-SEM) approach. The results revealed that "perceived learning value, perceived satisfaction, and personal innovativeness" are the most influential and critical determinants of students' intentions to use learning platforms through ChatGPT. This research contributes to the existing body of literature on AI and environmental sustainability, providing invaluable insights for practitioners, policymakers, and AI product developers. These insights can guide the development and implementation of AI technologies to better align with users' needs and preferences, while also considering the broader environmental context.

1. Introduction

Artificial intelligence (AI) has emerged as a groundbreaking tool, revolutionizing lives worldwide. A key illustration of this transformation is ChatGPT, or Chat Generative Pre-Trained Transformer. This tool is particularly crucial for its capability to assist students in generating term papers, short stories, explanations, and novels. The comprehensive reports and explanations furnished by this tool have ignited a wave of concern and apprehension at American University. The institution contends that this tool can craft paragraphs of acceptable quality, college-level research papers, and even answer test questions (McGee, 2023; Surameery & Shakor, 2023). The incorporation of natural language processing (NLP) models into the educational domain promises to markedly amplify the accessibility of information for educators, students, and academic staff. When juxtaposed with traditional tools like the Google platform, a distinct difference is the recent widespread acclaim attained by ChatGPT. Moreover, it offers a plethora of resources, encompassing books, articles, and websites. ChatGPT's ability to comprehend the intricacy of students' intentions and yield highly proficient responses empowers students to employ it for diverse purposes (McGee, 2023; Seth et al., 2023).

* Corresponding author.
E-mail address: kayoubi@hct.ac.ae (K. Ayoubi)

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ChatGPT's function has been scrutinized from multiple perspectives, encompassing medical, educational, and engineering viewpoints. Previous research has posited that the impact of ChatGPT permeates a broad spectrum of users, including students, doctors, patients, and others. Nonetheless, it is not devoid of limitations. There have been apprehensions articulated regarding ethical issues and creativity (Biswas, 2023; Khan et al., 2023; McGee, 2023; Qadir, 2022; Seth et al., 2023). Consequently, this study endeavors to investigate the determinants influencing students' acceptance of e-learning via ChatGPT and to ascertain how these determinants mold students' intentions to utilize ChatGPT.

In recent years, AI technologies, including ChatGPT, have drawn attention for their potential to revolutionize education by enabling personalized learning experiences. However, while the benefits of these technologies are widely recognized, there is a need for a more comprehensive understanding of the factors that influence their acceptance and use. This study contributes to the growing body of literature on this topic by examining the specific case of ChatGPT, a tool that has already shown promise in various applications but whose potential in the educational context is not yet fully understood. By exploring the factors that shape students' intentions to use ChatGPT, this study aims to provide valuable insights that can inform the development and implementation of AI-enabled learning tools in the future.

2. The Theoretical Framework

The current framework emphasizes how personal innovativeness mediates the relationships between perceived learning value and perceived satisfaction and the acceptance of learning platforms. Personal innovativeness serves as a mediator between the perceived learning value and perceived satisfaction and acceptance of learning platforms. Additionally, other relationships are also explored to assess the effectiveness of each platform, highlighting the advantages of using each platform.

2.1 The Perceived Satisfaction

Perceived satisfaction is defined as the degree to which technology users are satisfied with the implemented task and offered services. When users perceive technology to be satisfying, they are more likely to continue using it and recommending it to others. Conversely, when technology is perceived as dissatisfying, users may discontinue its use or seek out alternative options (Al-Azawei & Lundqvist, 2015; Navarro et al., 2021).

2.2 Perceived Learning Value

The perceived learning value, on the other hand, refers to the benefits that students perceive when using technology, such as access to information, time savings, and reduced effort. When students perceive high value in technology, they are more likely to continue using it over time. For educational institutions, perceived value is a crucial factor in establishing a competitive advantage through technology. By offering students a technology that provides clear benefits and advantages over other options, institutions can attract and retain students, enhancing their reputation and success. In summary, perceived value is an essential element for educational institutions seeking to implement an effective technological solution. By focusing on the benefits that students perceive they can gain from using the technology, institutions can create a strong competitive advantage that attracts and retains students over time (Alqurashi, 2019; Blau et al., 2020).

2.3 Personal Innovativeness

Personal innovativeness is considered a mediating factor that correlates the relation between the perceived usefulness and the perceived learning value and the acceptance of learning platforms. Thus, personal innovativeness is related to the users' willingness to adopt and use new technologies due to their innovative features that are not available in other technologies. It is a key factor in technology acceptance which measures the degree to which users are likely to seek out and experiment with new technologies (Gunasinghe et al., 2020).

Personal innovativeness and personal satisfaction can be closely related, as individuals with high levels of personal innovation may experience greater satisfaction when adopting and using new technologies. Innovativeness should meet the users' needs and expectations to fulfil the factor of satisfaction. Thus, personal innovativeness and personal satisfaction can be closely linked, with higher levels of personal innovativeness often associated with greater satisfaction in using new technologies. By designing technologies that meet the users' needs and expectations with high personal innovativeness, the acceptance of the technology will be higher and it may foster a sense of personal satisfaction and fulfilment among users (Aburayya et al., 2023; Almaiah et al., 2022; San-Martin & López-Catalán, 2013). Similarly, perceived learning value is closely related to perceived innovativeness. The users who perceive the technology as having a high learning value will pay attention to all the available features including personal innovativeness (Almaiah et al., 2022; Twum et al., 2022). Based on the previous assumptions, the following hypotheses are proposed:

H_1: *Perceived satisfaction of ChatGPT has a positive effect on perceived learning value of ChatGPT.*
H_2: *Perceived learning value of ChatGPT has a positive effect on personal innovativeness.*
H_3: *Perceived satisfaction of ChatGPT has a positive effect on personal innovativeness.*

H4: *Perceived learning value of ChatGPT has a positive effect on behavior intention to use learning platforms.*
H5: *Perceived satisfaction of ChatGPT has a positive effect on behavior intention to use learning platforms.*
H6: *Personal innovativeness of ChatGPT has a positive effect on behavior intention to use learning platforms.*

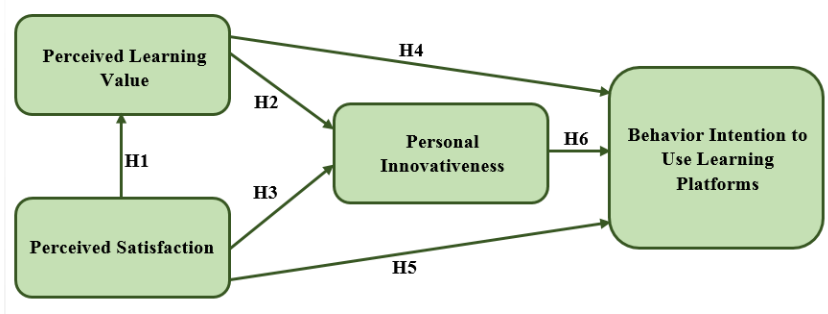

Fig. 1. Research Model.

3. Research Methodology

3.1 Data collection

Students from affiliated academic institutions in the United Arab Emirates (UAE) participated in online surveys. The data collection spanned from February 25, 2023, until June 30, 2023. The research committee distributed 300 surveys at random, achieving a 96.3% response rate from the distributed questionnaires. Of these, 289 were completed in their entirety, while 11 were discarded due to incomplete responses. The approved 289 questionnaires align with the recommended sample size of 285 participants out of a total population of 1100, as suggested by (Krejcie & Morgan, 1970). The selected sample size of 289 is significantly different from the minimum required sample size, enabling a PLS-SEM analysis (Salloum et al., 2021) to be conducted using this sample size to strengthen the hypotheses. It is vital to recognize that our assumptions are based on the historical context of artificial intelligence (Alshamsi et al., 2020). The research team utilized the PLS-SEM technique to evaluate their measurement model. Specifically, they chose the SmartPLS software, Version 3.2.7, for this analysis (Al-Maroof et al., 2021; Salloum et al., 2018). Once the initial assessment was completed, they proceeded to use the final path model, a sophisticated tool within SEM, to implement multifaceted interventions and gain deeper insights into their study.

This methodical approach ensured a comprehensive and accurate analysis of the data. A large and representative sample size was used, as advised by previous research, to increase the validity and generalizability of the study's findings. Additionally, the use of advanced analytical techniques, such as SEM and the Final Path Model, enabled a thorough examination of the relationships between variables and the assessment of complex interventions. Ultimately, this rigorous approach to data collection and analysis laid a solid foundation for the study's conclusions and recommendations, providing valuable insights into the factors influencing students' acceptance and use of AI-enabled learning tools like ChatGPT.

3.2 Demographic information

Fig. 2 presents a breakdown of the participants' demographics and personal information.

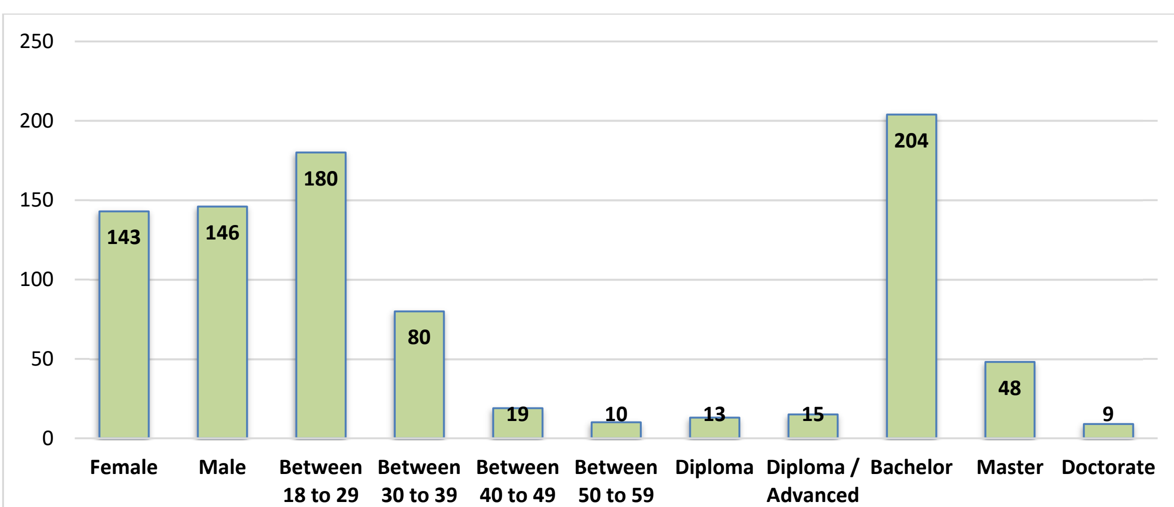

Fig. 2. Demographic data of the respondents (n=289)

It reveals that the respondents were almost evenly split by gender, with females representing 49% and males 51%. In terms of age, a majority (62%) of the students were between 18 and 29 years old, while the remainder were 29 or older. The participants' academic qualifications varied widely: 4% held a diploma, 5% an advanced diploma, 71% an undergraduate degree, 17% a postgraduate degree, and 3% a doctorate. When participants expressed willingness to volunteer, the "purposive sampling method" suggested by (Salloum & Shaalan, 2018) was implemented. The study included participants from multiple universities, encompassing a broad range of ages and educational backgrounds.

3.3 Study Instrument

In the ongoing study, a questionnaire was employed to validate the proposed theory. Four factors were carefully selected as reliable indicators, leading to the inclusion of 11 fresh components in the questionnaire. The foundation of these factors is outlined in Table 1, aimed at enhancing the usefulness of the research factors and providing supportive data from a wide range of existing studies that reinforce the current framework. In the end, the research team made necessary adjustments to the questionnaire items, informed by previous research.

Table 1
Measurement Items

Constructs	Items	Instrument	Sources
Behavior Intention to Use Learning Platforms	INU1	ChatGPT offers a good opportunity to try.	(Davis, 1989, 1993)
	INU2	ChatGPT presents a valuable chance to experiment.	
The Perceived Satisfaction	SAT1	ChatGPT has more satisfactory tools that facilitate the process of learning.	(bin Abdullah, 2021)
	SAT2	ChatGPT has innovative features that affect my level of satisfaction.	
	SAT3	ChatGPT does satisfy my learning needs to adopt it.	
The Perceived Learning Value	LVL1	ChatGPT offers more significant benefits in my learning process.	(Alqurashi, 2019; Blau et al., 2020)
	LVL2	ChatGPT has a special type of value in different learning task.	
	LVL3	ChatGPT does have a unique value which encourages me to adopt the technology.	
Personal Innovativeness	INN1	ChatGPT has an up-to-date technology that satisfies my needs.	(Gunasinghe et al., 2020)
	INN2	ChatGPT has more innovative features that increase the value of the technology.	
	INN3	ChatGPT provides me with a higher level of unique experience that encourages me to adopt it.	

4. Findings and Discussion

4.1 Data Analysis

The present study utilized PLS-SEM via SmartPLS V 3.2.7 (Habes et al., 2022; Ringle et al., 2015) for analyzing the data. This process involved a two-step assessment methodology, incorporating both the measurement and structural models (Hair et al., 2017). Several key reasons, outlined throughout the paper, justified the selection of PLS-SEM for this research. First, it was crucial to analyze the proposed conceptual theory using PLS-SEM (Urbach & Ahlemann, 2010). Second, PLS-SEM proved effective in managing the exploratory research data collected from the conceptual models (Hair Jr et al., 2016). Third, the analysis using PLS-SEM was conducted on the entire model as a cohesive whole, instead of dissecting it into distinct segments (Goodhue et al., 2012). Lastly, a simultaneous analysis was performed on both the structural and measurement models using PLS-SEM. The importance of PLS-SEM is underscored by its capacity to generate and yield precise measurements (Barclay et al., 1995).

4.2 Convergent validity

The evaluation of the Measurement Model (Hair et al., 2017) was conducted based on the principles of construct validity, which includes both discriminant and convergent validity, as well as construct reliability, encompassing Cronbach's alpha (CA) and composite reliability (CR). Table 3 illustrates that Cronbach's alpha (CA) values, which signify construct reliability, ranged from 0.861 to 0.879. These values are below the recommended threshold of 0.7 (Nunnally & Bernstein, 1994). However, the data in Table 3 also indicate that the composite reliability (CR) scores ranged from 0.818 to 0.863, surpassing the specified threshold. To assess convergent validity, it is crucial to examine the average variance extracted (AVE) and factor loadings (Hair et al., 2017). Besides the values previously mentioned, Table 3 shows that all factor loading values exceeded the criterion value of 0.7. Additionally, Table 3 presents the AVE values, which surpass the 0.5 benchmark, despite the earlier values ranging from 0.695 to 0.724. Therefore, based on the above considerations, it is reasonable to conclude that convergent validity was achieved.

4.3 Discriminant validity

To assess the discriminant validity, the study opted to reevaluate two criteria using the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larker criterion (Hair et al., 2017). The results, detailed in Table 4, clearly indicate that the Fornell-Larker criterion validates the criteria, as each Average Variance Extracted (AVE) and its square root exhibit stronger associations with their respective constructs (Fornell & Larcker, 1981).

Table 5 clarifies the results of the HTMT ratio, where each construct falls below the '0.85' threshold (Henseler et al., 2015). This indicates that the HTMT ratio meets the specified criterion, enabling the determination of discriminant validity. The findings of this study verify that there were no issues regarding the validity and reliability assessment of the Measurement Model. Consequently, the gathered data can be effectively utilized for the analysis of the structural model. This rigorous approach to validating the criteria and ensuring the absence of complications in the assessment of the Measurement Model's validity and reliability underscores the robustness of the study's methodology. It ensures that the data used for evaluating the structural model is of high quality, thereby enhancing the overall credibility and validity of the research findings.

Table 3
Convergent validity results

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Behavior Intention to Use Learning Platforms	INT1	0.799	0.875	0.855	0.724
	INT2	0.783			
Personal Innovativeness	INQ1	0.873	0.879	0.818	0.695
	INQ2	0.791			
	INQ3	0.836			
Perceived Learning Value	SYQ1	0.812	0.873	0.830	0.709
	SYQ2	0.755			
	SYQ3	0.821			
Perceived Satisfaction	TEC1	0.863	0.861	0.863	0.720
	TEC2	0.819			
	TEC3	0.841			

Table 4
Fornell-Larcker Scale

	INU	INN	LVL	SAT
INU	**0.807**			
INN	0.523	**0.843**		
LVL	0.601	0.259	**0.833**	
SAT	0.310	0.313	0.181	**0.799**

Table 5
Heterotrait-Monotrait Ratio (HTMT)

	INU	INN	LVL	SAT
INU				
INN	0.493			
LVL	0.621	0.563		
SAT	0.321	0.363	0.519	

4.4 Hypotheses testing

The structural model in this study was constructed using Smart PLS, a tool that utilizes maximum likelihood estimation to examine the relationships among various theoretical constructs within the structural model (Alfaisal et al., n.d.; Alhumaid et al., 2022). This method enabled the analysis of the proposed hypotheses, the outcomes of which are detailed in Table 6 and Figure 3, demonstrating the model's moderate predictive power (Chin, 1998). Table 7 encompasses the beta (β) values, t-values, and p-values of all the developed hypotheses, as deduced from the PLS-SEM technique. A comprehensive analysis of the empirical data substantiated the hypotheses H1, H2, H3, H4, H5, and H6.

The inaugural hypothesis probed the association between SAT and LVL, exhibiting a β value of 594 and a p-value less than 0.05. This result underscores a notable positive impact of SAT on LVL, thereby validating H1. Additionally, the findings reveal that INN is markedly influenced by both LVL ($\beta = 0.646$, $P < 0.05$) and SAT ($\beta = 0.708$, $P < 0.01$), thereby substantiating hypotheses H2 and H3. This affirms the significant ramifications of LVL, SAT and INN on INU. The study's outcomes also unveil substantial correlations between INU and several factors. Specifically, INU exerted a significant positive effect on LVL ($\beta = 0.373$, $P < 0.001$). Moreover, the study deduced that both SAT ($\beta = 0.692$, $P < 0.01$), and INN ($\beta = 0.851$, $P < 0.01$) wield a considerable influence on INU. Consequently, hypotheses H4, H5, and H6 garnered support in this investigation.

Table 6
R^2 of the endogenous latent variables

Construct	R^2	**Results**
INU	0.621	Moderate
INN	0.636	Moderate
LVL	0.512	Moderate

Table 7
Hypotheses-testing

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H_1	SAT → LVL	0.594	8.248	0.032	Positive	Supported*
H_2	LVL → INN	0.646	9.559	0.020	Positive	Supported*
H_3	SAT → INN	0.708	11.386	0.003	Positive	Supported**
H_4	LVL → INU	0.373	17.453	0.000	Positive	Supported**
H_5	SAT → INU	0.692	12.576	0.004	Positive	Supported**
H_6	INN → INU	0.851	15.413	0.001	Positive	Supported**

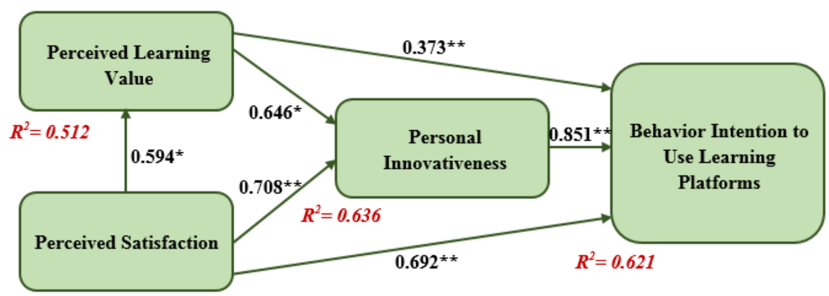

Fig. 3. Path coefficient of the model (significant at p** < = 0.01, p* < 0.05)

5. Conclusion

ChatGPT holds a critical role in higher education by delivering personalized and effective learning experiences. It could produce customized feedback and explanations, aiding students in creating term papers, short stories, and even understanding intricate concepts. The incorporation of ChatGPT not only amplifies the accessibility of information for educators and students but also metamorphoses the conventional classroom setup into a more vibrant and engaging environment. It can decipher the intricacy of students' intentions and furnish highly proficient responses, thereby empowering students to utilize it for diverse educational objectives. Furthermore, it harbors the potential to revolutionize e-learning by providing a more interactive and tailored learning experience, thereby fostering students' acceptance and intention to utilize AI-powered tools like ChatGPT in their educational journey. The findings demonstrated that perceived learning value, perceived satisfaction, and personal innovativeness are the most crucial and significant predictors of students' intentions to employ ChatGPT for learning platforms. However, this study is not without its limitations. The data was gathered from a specific cohort of students in the UAE, and the results may not be applicable to other populations or contexts. The participants primarily comprised students from various universities in the UAE, who utilize the applications for diverse educational objectives. Future research could center on samples from other government institutions or different geographical locations to broaden the understanding of ChatGPT usage. Additionally, the conceptual framework of this study is confined to specific aspects related to perceived learning value, perceived satisfaction, with a moderator measuring the effects of ChatGPT. Subsequent research could include other variables and different moderators to assess other essential factors that may impact the acceptance and usage of ChatGPT.

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