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STUDENTS' ACCEPTANCE OF AI-BASED CHATGPT FOR EDUCATION: A COMPREHENSIVE ANALYSIS USING PLS-SEM

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ABSTRACT

Artificial intelligence (AI) is transforming a number of aspects of human existence, including science, psychology, the arts, healthcare, education, and various other fields. The enormous influence of AI is seen in how it changes how we approach and engage with all of these sectors. One of the AI-based software programmes featuring a conversational AI interface is ChatGPT, an OpenAI chatbot. As one of the most groundbreaking applications, ChatGPT has attracted a lot of interest from the general public on a global scale. By using ChatGPT, the teaching and learning process in education could potentially be enhanced. Prior research mostly focused on academics' and scientists' opinions on ChatGPT and its future, while giving less importance to students' perspectives on ChatGPT adoption. Therefore, the objective of this study is to understand the variables that influence students' adoption of ChatGPT for their education. A "Students' Adoption of AI" model, which helps in assessing behavioural intention and use behaviour, is proposed in this study and is based on the traditional Unified Theory of Acceptance and Use of Technology (UTAUT) model. The constructs of the proposed model are performance expectancy, effort expectancy, social influence, and facilitating conditions. The construct validity and reliability of the model are evaluated, and it is then further examined using PLS-SEM for hypothesis estimation and prediction.

Keywords: ChatGPT, Artificial Intelligence, Acceptance, Behavioral Intention, Influence, Education

1. INTRODUCTION

The term "Artificial Intelligence" (AI) refers to systems that mimic human cognition and decision-making. AI, which uses machine learning, neural networks, and natural language processing to address a variety of issues, involves the science and engineering for developing intelligent computers. It is transforming all aspects of life, including science, psychology, and medicine. Today, we have programmes that can discover new medicine formulas predict elusive protein structures and write full-length stories

The pandemic has created interest in artificial intelligence in education, which offers personalised teaching that is available anytime. Despite widespread excitement about how AI may transform education, caution is recommended in light of concerns about privacy, bias, and excessive reliance on technology. Maintaining a balance is necessary to promote ethical and fair AI integration in education. With the use of chatbots and other technologies, AI may assist teachers in keeping track of students' progress and performance, recommending educational materials, and automating assessments.

OpenAI released ChatGPT (Generative Pre-trained Transformer) in November 2022. The intelligent replies that ChatGPT generates are logical, relevant, and fluent. It could assist with many tasks, such as writing essays, formulating research topics, doing literature reviews, enhancing documents, and writing computer code (Shoufan, 2023). The teaching and learning processes in education might be revolutionised by ChatGPT.

Studies have discussed ChatGPT's educational advantages and some have offered suggestions on how to incorporate it in the classroom. Many studies have examined the use of ChatGPT in medical education (Gilson et al., 2023; Strzelecki, 2023), academic writing, publication, authorship, and other general topics, and an analysis of Twitter opinion on the adoption of ChatGPT in general (Haque et al., 2022). Few studies have been done on the use of ChatGPT in education. This is because ChatGPT has only just been established, and its potential in education remains to be investigated.

There are many possibilities for studying its usage and acceptance. The usage of ChatGPT in general education was investigated in a recent study, with an emphasis on its advantages and potential drawbacks. The review of the literature found a research gap where prior studies preferred to give greater importance to scientists' and academic teachers' viewpoints on ChatGPT and its future, whereas giving less attention to students' perspectives on ChatGPT adoption. Considering that the AI tool has just recently been established, there is limited information available on its adoption and how it is utilised by students. The objective of this research is to understand the factors that influence students' adoption of ChatGPT for their education.

2. THEORETICAL FRAMEWORK

Over the past twenty years, numerous research studies have explored the factors influencing people's willingness to embrace new technologies, particularly in the realm of e-learning. Among these, the Unified Theory of Acceptance and Use of Technology (UTAUT) model, introduced by Venkatesh et al. in 2003, has emerged as a robust framework for understanding behavioral intentions in this context. Key factors within the UTAUT model include performance expectancy, effort expectancy, social influence, and facilitating conditions, which are considered independent variables. These variables are believed to influence individuals' behavioral intentions and actual usage behavior regarding technology adoption. Additionally, moderators such as age, gender, prior technology experience, and voluntariness of usage have been identified as factors shaping these relationships. To delve into the specific factors driving students' adoption of ChatGPT for educational purposes, this study proposes a model the "Students' Adoption of AI" model, drawing upon the UTAUT framework. This model aiming to understand how these elements influence students' decisions to embrace AI technology for learning purposes. The constructs of the prosed model are addressed below:

2.1. PERFORMANCE EXPECTANCY (PE)

Performance expectation (PE) is the belief that using a certain technology will increase one's performance (Venkatesh et al., 2003). People will accept new technology if it makes their tasks simpler and more effective (Davis, 1989). With the aid of e-learning, students may raise their productivity by performing better and finishing their tasks more quickly (Al-Shahrani, 2016; Al-Qeisi et al., 2015). Performance expectation, as used in this study, is the notion believed by students that utilising ChatGPT will enhance their academic performance. The Following hypothesis is proposed,

H1: Performance expectancy (PE) has positive effect on Behavioral intention (BI)

H2: Performance expectancy (PE) has positive effect on Use behavior (UB)

Table 1

Table 1 Convergent validity

Construct	Indicator	Outer loadings	Cronbach's Alpha	Composite reliability	Average Variance Extracted (AVE)
Behavioural Intention	BI1	0.913	0.908	0.942	0.845
	BI2	0.920			
	BI3	0.925			
Effort Expectancy	EE1	0.883	0.892	0.925	0.755
	EE2	0.851			
	EE3	0.875			
	EE4	0.868			
Facilitating Conditions	FC1	0.905	0.837	0.847	0.757
	FC2	0.903			
	FC3	0.798			
Performance Expectancy	PE1	0.846	0.909	0.936	0.787
	PE2	0.913			
	PE3	0.921			
	PE4	0.866			
Social Influence	SI1	0.876	0.869	0.911	0.719
	SI2	0.862			
	SI3	0.856			
	SI4	0.796			
Use Behavior	UB1	0.849		0.918	0.737
	UB2	0.847	0.881		
	UB3	0.890			
	UB4	0.845			

2.2. EFFORT EXPECTANCY (EE)

Effort expectancy, as defined by Venkatesh et al. (2003), pertains to the level of effort required to utilize a particular technology. The acceptance of mobile learning and learning management systems was impacted by individuals' perceptions of the effort involved, as indicated by Hu et al. (2020). If a potential user believes that the offered technology is valuable but that using the system would involve a significant amount of work, the performance benefits of utilization will be outweighed (Davis 1989). In order to predict behavioural intention, effort expectancy is a key variable (Salloum & Khaled Shaalan 2018). In this study, the extent to which students perceive ChatGPT as user-friendly and requiring minimal effort for interaction is crucial. Effort expectancy plays a significant role in influencing performance outcomes (Ugur & Turan, 2021).

H3: Effort Expectancy (EE) has positive effect on Behavioral Intention (BI)

H4: Effort Expectancy (EE) has positive effect on Performance Expectancy (PE)

Table 2

Table 2 Fornell & Larcher

Constructs	BI	EE	FC	PE	UB
BI	0.919				
EE	0.674	0.869			
FC	0.651	0.632	0.870		
PE	0.610	0.841	0.611	0.887	
UB	0.817	0.718	0.740	0.698	0.858

2.3. SOCIAL INFLUENCE (SI)

Social influence, as defined by Venkatesh et al. (2003), relates to the extent to which an individual's technology usage is shaped by the influence of others. This influence extends to the behavioral intention to utilize e-learning, given that instructors, seniors, friends, and other significant individuals may impact the acceptance of e-learning, as noted by Wang et al. (2009). In the context of this study, the term "social influence" pertains to the perceived level of support or encouragement from friends, teachers, or other influential figures within students' social circles regarding the use of ChatGPT.

H5: Social Influence (SI) has positive effect on Behavioral Intention (BI)

Table 3

Table 3 R square

Construct	R-square	R-square adjusted
BI	0.551	0.546
PE	0.711	0.710
UB	0.770	0.767

2.4. FACILITATING CONDITIONS (FC)

Facilitating conditions (FC), as described by Venkatesh et al. (2003), gauge the extent to which a user believes there exists a technological and institutional infrastructure to facilitate the adoption of technology. Effective utilization of e-learning necessitates adequate technological support, as highlighted by Salloum & Khaled Shaalan (2018) and Abbad (2021), along with internet accessibility. In the context of this study, FC pertains to students' perceptions regarding their access to the AI tool, as well as the availability of training and technical assistance for ChatGPT.

H6: Facilitating Condition (FC) has positive effect on the Use Behaviour (UB)

Table 4

Table 4 Model fitness

	Saturated Model	Estimated Model
SRMR	0.053	0.067
NFI	0.844	0.837

2.5. BEHAVIOURAL INTENTION (BI)

Behavioral intention, as defined by Venkatesh & Xu (2012) and Davis (1986), denotes the individual's subjective inclination or likelihood to utilize a particular technology in the future. In the context of this study, "behavioral intention" pertains to a student's intention to incorporate ChatGPT into their educational activities.

H7: Behavioural Intention (BI) has positive effect on the Use Behaviour (UB)

2.6. USE BEHAVIOUR (UB)

Use behavior, as described by Venkatesh & Davis (2012), signifies the practical application of technology by an individual subsequent to forming a behavioral intention to use it. In the context of this study, "UB" denotes the extent to which students actively employ ChatGPT in their academic endeavors.

3. RESEARCH METHODOLOGY

For this study, a quantitative research approach was adopted, involving a sample of 251 students from southern India. The participants were specifically those who had utilized ChatGPT for educational tasks like learning or seeking clarification. Data collection was conducted through a structured questionnaire, encompassing demographic details of the respondents alongside inquiries regarding model variables. Responses were recorded using a five-point Likert scale, where 1 indicated "strongly disagree," 2 indicated "disagree," 3 indicated "neutral," 4 indicated "agree," and 5 indicated "strongly agree."

4. DATA ANALYSIS

4.1. DEMOGRAPHIC PROFILE OF THE RESPONDENTS

The questionnaire was provided to respondents, using Google Forms in early June 2023. The survey was available for a week. There were 251 responses, with males contributing the majority (71.70%) and women (28.030%).

4.2. MEASUREMENT MODEL ANALYSIS

The reliability of the scale was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR) tests, with recommended values exceeding 0.7. CA ranged from 0.837 for FC to 0.909 for PE, indicating acceptable internal consistency across all constructs in the proposed model. CR values ranged from 0.847 (FC) to 0.942 (BI). Convergent reliability was evaluated through Average Variance Explained (AVE) and item loading, both surpassing the recommended thresholds of 0.5 and 0.708, respectively, for all constructs, as indicated in Table 1. Discriminant validity was confirmed when the square root of AVE for each construct exceeded its correlation with other constructs. This criterion was met, as shown in Table 2, demonstrating the discriminant validity of the measurement model.

Coefficient of Determination (R Square) assessed parameter accuracy, with results exceeding 0.5 considered acceptable and those surpassing 0.7 deemed significant. PE and UB yielded significant results of 0.711 and 0.770, respectively, while BI achieved an acceptable result of 0.551, as displayed in Table 3. Model fitness was evaluated using Standardized Root Mean Square Residual (SRMR) and Norm Fit Index (NFI), with an optimal SRMR below 0.1 and NFI values ranging from 0 to 1. The model met fitness criteria with SRMR and NFI results of 0.053 and 0.844, respectively, as detailed in Table 4.

Table 5

Table 5 Hypothesis testing

Hypothesis	Constructs	Path	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1	PE -> BI	-0.064	-0.068	0.12	0.535	0.593	Not Supported
H2	PE -> UB	0.225	0.224	0.055	4.088	0	Supported
H3	EE -> BI	0.282	0.283	0.115	2.462	0.014	Supported
H4	EE -> PE	0.843	0.844	0.023	36.526	0	Supported
H5	SI -> BI	0.55	0.554	0.082	6.736	0	Supported
H6	FC -> UB	0.277	0.277	0.057	4.867	0	Supported
H7	BI -> UB	0.499	0.501	0.063	7.911	0	Supported

4.3. STRUCTURAL MODEL ANALYSIS

The proposed model underwent analysis using PLS-SEM, with further validation carried out using the bootstrapping method as outlined by Henseler et al. (2009). The anticipated relationship between Performance Expectation (PE) and Behavioral Intention (BI), referred to as H1, did not yield significance (ß= -0.064, t=0.535, p=0.593), indicating that H1 is not substantiated, as presented in Table 5. The proposed relationship between Performance Expectation (PE) and Use Behaviour (UB) is labelled H2 and indicates significance (ß=0.225, t=4.088, p=0.000) demonstrating that H2 is supported. H3 represents the hypothesised relationship between Effort Expectations (EE) and Behavioural Intentions (BI), which was not significant (ß=0.282, t=2.462, p=0.014) demonstrating that H3 is not supported. The proposed relationship between Effort Expectations (EE) and Performance Expectation (PE) is labelled H4 and indicates significance (ß=0.843, t=36.526, p=0.000) demonstrating that H4 is supported. Hypothesized association between Social Influence (SI) and Behavioural Intention (BI) is denoted as H5 and shows significance (ß=0.550, t=6.736, p=0.000) demonstrating that H5 is supported. Hypothesized relationship between Facilitating Conditions (FC) and Use Behaviour (UB) is labelled H6 and shows significance (ß =0.277, t=4.867, p=0.000) this shows that H6 is supported. Hypothesized relationship between Behavioural Intention (BI) and Use Behaviour (UB) is labelled as H7 and shows significance (ß=0.499, t=7.911, p=0.000), and this indicates that H7 is supported.

5. CONCLUSION

The findings reveal that students perceive ChatGPT usage as requiring minimal effort, which positively impacts their performance and encourages further adoption of the technology. Notably, social influence emerges as the most influential factor affecting the intention to adopt ChatGPT, followed by effort expectancy and facilitating conditions. Given the early stages of ChatGPT and AI development, there remains ample room for exploring their potential applications in education.

6. LIMITATIONS AND FUTURE STUDY

Expanding the study's geographical scope to include samples from diverse locations could provide a more comprehensive understanding of ChatGPT acceptance. Furthermore, while the study employed a quantitative methodology, future research might consider incorporating qualitative methods or adopting a mixed-methods approach to deepen insights into ChatGPT adoption and its implications in education.

CONFLICT OF INTERESTS

None.

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