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Exploring Factors Influencing Nigerian Higher Education Students to Adopt ChatGPT in Learning

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ABSTRACT

This study explores factors influencing Nigerian Higher Education students to adopt ChatGPT in learning. Using the technology acceptance model (TAM), this research aims to identify the key factors influencing the behavioural intentions of Nigerian undergraduate students to adopt ChatGPT in their academic pursuits. This study's theoretical foundation is rooted in the TAM which explores how users perceive and accept technology. The research model includes constructs such as perceived usefulness, perceived ease of use, perceived risk, personal innovativeness, social influence, behavioural intention, and use behaviour. The study used a structured and duly validated questionnaire based on the TAM constructs and employed partial least squares structural equation modelling (PLS-SEM) for data analysis. The analysis of findings reveals significant factors influencing the adoption of ChatGPT among Nigerian undergraduate students, providing insights into the perception and awareness of the use of ChatGPT in an educational context. The study's implications and conclusions contribute to the understanding of the implications of integrating advanced AI, such as ChatGPT, into educational settings, addressing concerns related to academic integrity, critical thinking skills, and the quality of learning outcomes. The research also sheds light on the ethical considerations and policy development necessary for the balanced integration of AI-assisted learning in educational institutions.

Keywords: *Artificial Intelligence (AI); ChatGPT; Large Language Models (LLM); Perceived usefulness; Perceived ease of use; Perceived risk; Personal Innovativeness; Social Influence; Behavioural Intention and Use Behaviour.*

INTRODUCTION

ChatGPT is a family of generative AI that allows users to instruct and get humanlike responses instantly. The growing importance of artificial intelligence (AI) in the field of education has raised concerns about its possible implications on the overall performance of students, especially concerning the use of large language models (LLM) like ChatGPT (Tanvir et al., 2023). With its remarkable accessibility and powerful capabilities made accessible to the wider public, OpenAI's ChatGPT has become a prominent participant in the AI arena (Wu et al., 2023). Thanks to its remarkable fluency and versatility in language, it can do a wide range of tasks, including summarising documents, providing replies across several disciplines, and even penning articles on diverse subjects (Ray, 2023). Furthermore, ChatGPT has been widely used in educational settings to enhance learning experiences and support personalised instruction. Its ability to generate coherent and contextually relevant responses makes it a valuable tool for students seeking academic assistance.

Additionally, the integration of ChatGPT into educational platforms has facilitated seamless interactions between students and the AI system, promoting engagement and knowledge acquisition (Fergus et al., 2023). However, there is a risk of plagiarism, as students may be tempted to directly copy and paste the ChatGPT-generated answers without fully understanding the concepts. It is important for educators and parents to encourage a balanced approach where ChatGPT is used as a helpful resource alongside traditional learning methods, fostering a deeper understanding of the material. Furthermore, Farrokhnia et al. (2023) argued that while ChatGPT streamlines the process of finding information and solutions, it may stifle students' creative thinking and research skills, potentially impeding their ability to generate original ideas and contribute to academic discourse.

However, Mishra et al. (2023), opined that relying solely on ChatGPT for answers may limit students' exposure to diverse perspectives and alternative viewpoints, hindering their ability to think critically and engage in meaningful discussions. Furthermore, without developing their own research skills, students may struggle to evaluate the credibility and reliability of information obtained from the AI system, leading to potential inaccuracies in their work. Furthermore, the sheer accessibility of ChatGPT has fuelled its popularity, amassing a vast user base (Mishra et al.,2023). However, this accessibility has also given rise to concerns surrounding academic integrity. Some students may be tempted to employ AI assistance for completing assignments and exams, potentially diminishing the value of authentic learning experiences. Furthermore, the reliance on ChatGPT for academic tasks may hinder students' critical thinking abilities and critical thinking skills. Instead of grappling with complex concepts and engaging in rigorous analysis, students may opt for quick answers provided by the AI model. This could undermine their overall educational development and limit their ability to think independently.

The integration of advanced AI, exemplified by an LLM like ChatGPT, into educational contexts, has introduced a range of multifaceted challenges and concerns that warrant careful examination (Tanvir et al., 2023). This integration has sparked both enthusiasm and concern within educational institutions, leading to pressing questions about its perception and awareness of its usage amongst students. Moreso, the utilization of AI, particularly LLM like ChatGPT, within the realm of education has introduced pressing issues such as the compromise of academic integrity, potential hindrance to critical thinking skills, questions about the quality of learning outcomes when AI is used, and concerns about the accuracy and authenticity of academic work (Ray, 2023). Furthermore, the extent to which AI influences students' performance, both positively and negatively, is a subject of exploration. Ethical considerations, policy development, and the balance between providing support and fostering students' autonomy in the context of AI-assisted learning are also pivotal aspects of this complex issue.

Scholars have examined students' academic integrity influenced by ChatGPT (De Angelis et al., 2023); Alkaissi & McFarlane, 2023; Arianna, 2023). Others investigated how ChatGPT can influence student's academic performance (Tanvir et al. (2023). While scholars have examined the influence of ChatGPT on students' academic performance across various contexts, there is paucity of such a scholarly endeavour in Nigeria. Therefore, the context in which the current study is undertaken within the context of Nigerian universities. The current study considers the perception and awareness of the use of ChatGPT among undergraduate students in Nigerian universities. Analysis in this study will focus on the significant variables that influence the adoption of ChatGPT among Nigerian undergraduate students from an educational standpoint. Specifically, this study's main objective is to determine the key factors that influence the behavioural intentions of Nigerian undergraduate students to adopt ChatGPT in their academic pursuits. The theoretical foundation, literature review and formulation of research are presented in the next section, followed by the data analysis, findings and discussion. The conclusions and suggestions for further research are also reported.

THEORETICAL FOUNDATION

The technology acceptance model (TAM) studies how users perceive and accept technology (Lee & Lehto 2013). TAM is a known socio-model that aims to explain why people embrace certain technologies (Granić & Marangunić 2019). According to TAM, an individual's willingness to use a technology is measured by their intentions to use it (Lee & Lehto, 2013). These intentions are influenced by people's attitudes, towards the technology and their perception of its usefulness (Davis et al., 1989). Attitude toward technology reflects an individual's emotional responses and evaluations of its use, closely linked to their motivation (Ajzen, 1991; Lee & Lehto, 2013).

This emotional stance is closely tied to motivation, as people with a positive attitude toward a technology are more likely to have intentions of using it (Davis et al., 1989; Estriegana et al., 2019). The perceived usefulness of a technology is a key factor, representing an individual's belief in how much using the technology will enhance their performance (Davis, 1989). However, external motivation also plays a crucial role in determining technology acceptance and use. For instance, if students believe that incorporating technology into their writing will improve their performance, they are more likely to develop a positive attitude towards using it. The perceived usefulness of the technology further influences attitudes and subsequently impacts intentions. When students see technology as valuable for enhancing their skills, they are more inclined to view it positively and be more willing to incorporate it into their learning.

This research used the TAM-ChatGPT framework because of its support in the investigation of factors responsible for the adoption of new technologies. It is also termed TAM-ChatGPT framework because of the modifications to the original TAM by incorporation of other factors such as perceived risk (PR) (an inhibitor) as predictors of the intention to use ChatGPT and personal innovativeness (PI) that serves as the key determinant of ChatGPT perceived usefulness (CPU) and ChatGPT Perceived ease of use (CPEU).

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

ChatGPT Perceived Usefulness (CPU)

Several previous studies have evaluated the practicality of ChatGPT using a five-item scale adapted from Davis (1998) and Rafique et al (2020). These studies have shown that the scale is reliable and valid. The findings indicate a correlation, between the perceived usefulness of ChatGPT and students' intention to use it as well as their attitude towards its usage. Additionally, there is a correlation between the perceived ease of use of ChatGPT and its perceived usefulness and attitude towards usage. It was also observed that previous experience, with ChatGPT influenced how easily it was perceived to be used. Overall, these studies suggest that students are highly inclined to utilize ChatGPT for writing and complex thinking purposes.

H1. Perceived usefulness positively impacts the behavioural intention to adopt ChatGPT.

ChatGPT Perceived Ease of Use (CPEU)

The concept of perceived ease of use refers to how a person believes they can use a technology without much effort. In the case of ChatGPT, studies have shown that there is a positive correlation, between perceived ease of use and students' intention to use ChatGPT for writing purposes (Zou 2023, Yilmaz et al. 2023). Additionally, it has been found that perceived ease of use is also strongly and positively related to how useful students perceive ChatGPT to be. To measure perceived ease of use, researchers used a five-item scale adapted from Davis and the results indicated that the scale had validity in assessing this construct (Zou 2023).

The ease of using ChatGPT plays a role, in how users perceive and adopt the technology and the degree to which users find ChatGPT easy to use is a factor influencing their acceptance and adoption of the technology.

H2. The perceived ease of use positively influences the perceived usefulness of ChatGPT.

Perceived Risks (PR)

There are risks involved in using ChatGPT that require consideration. These risks encompass the possibility of receiving unhelpful responses, potential security threats, like exposing information and the chance of biased or inappropriate answers. Furthermore, concerns arise regarding the stage of this technology, governance and usage guidelines as well as limitations in data, security measures and analytics. Legal and compliance leaders have identified six risks associated with ChatGPT including the generation of incorrect answers, potential violations of intellectual property rights and copyrights as well as risks to consumer protection. It is crucial for individuals and organizations to be aware of these risks and establish guidelines for using ChatGPT in order to minimize any negative impacts (Munir 2023, Cuomo 2023, and Stamford, Conn. 2023).

H3. "Perceived risks (PR) significantly and negatively affect perceived usefulness (PU)."

H4. "Perceived risks (PR) significantly and negatively affect behavioural intention (BI) to use ChatGPT.

Personal Innovativeness (PI)

Personal innovativeness refers to an individual's openness to imagine and embrace creative ways of thinking utilizing technology or embracing products and services. It can also be associated with responses towards products and how consumers behave. Research has indicated that perceived brand innovativeness strongly correlates with reactions towards a product design influencing consumer behaviour and purchase intention. Consumer innovativeness signifies a propensity to buy unique products, which in turn influences consumers' knowledge and purchasing decisions regarding products or brands. Perceived innovativeness plays a role, in driving the adoption of products and services while also impacting user behaviour and preferences (Lowe 2015, Kaplan 2009, Colman et al. 2019).

Moreover, according to a study conducted by Sitar-Taut & Mican (2021) personal innovativeness and openness to ideas are factors influencing the acceptance of mobile learning in times of social distancing. In this study, personal innovativeness refers to the extent to which students are willing to adopt innovative technological tools such as ChatGPT and their belief, in their ability to learn and excel at acquiring new technological skills. The following hypothesis has been put forth;

H5. Personal innovativeness has direct and significant impact on Use behaviour.

Social Influence (SI)

The utilization of ChatGPT, an AI language model is impacted by various factors. There are outcomes associated with its use, including enhanced customer service, cost savings, personalised learning experiences and more efficient interactions on social media platforms (Ahmad 2023, AIContentfy team 2023). However, there are also concerns regarding effects like the dissemination of misinformation, biased content, and job displacement (Menon & Shilpa 2023, Gebby 2023; Ahmad 2023). Additionally, ethical considerations arise concerning privacy violations, news dissemination and employment consequences (Gebby 2023, Ahmad 2023). Individuals, organizations, and society as a whole, must consider these implications to ensure proper usage of this technology (Ahmad 2023).

H6. Social influence positively impacts the behavioural intention to use ChatGPT.

Behavioural Intention (BI)

Various factors influence people's inclination to use ChatGPT according to research. Key determinants, for using ChatGPT include things like how easy it is to use, how well it performs, the motivation and value people see in it as well as their attitudes towards the technology. The Technology Acceptance Model (TAM) suggests that people's actual usage of technology is linked to their intentions, which are shaped by factors like usefulness, ease of use and attitudes towards the technology (Habibi et al 2023, and Zou et al 2023).

Studies also reveal that students and users generally have intentions, attitudes, and perceptions of usefulness and ease of use when it comes to ChatGPT. This indicates an inclination towards using this technology (Zou et al. 2023, Shahsavar & Choudhury 2023). Furthermore, positive experiences with decision-making while using ChatGPT have been found to increase people's intention to use it for self-diagnosis and health-related purposes (Shahsavar & Choudhury 2023).

To crown it all, the intention to use ChatGPT is influenced by factors such as perceived usefulness, ease of use, attitudes towards the technology itself, performance expectations and facilitating conditions. These findings provide insights into what drives intention when it comes to using ChatGPT, in educational and health-related settings.

Use Behaviour (UB)

The use and adoption of ChatGPT, an AI language model have been extensively studied in contexts including education and behaviour analysis. Research indicates that several factors influence users' intention to use ChatGPT, such, as their expectations of its performance, perceived usefulness, ease of use, attitude towards ChatGPT usage and prior experience with it. For instance, a study focusing on the acceptance of ChatGPT among students in writing reveals that students expressed intentions towards using ChatGPT due to their favourable attitudes, perceived usefulness and ease of use (Zou et al, 2023, Strzelecki 2023). Furthermore, ChatGPT's potential for enhancing learners' self-regulation has been explored in the field of behaviour analysis (Chung Yee Lai 2023). These findings highlight a growing interest in and acceptance of ChatGPT, across domains driven by its perceived usefulness and user-friendly interface.

MEASUREMENT SCALE

The structured questionnaire entitled Perception and Awareness of the use of ChatGPT in Learning and Research Questionnaire (PAUCLRQ) serves as the primary tool for data collection in this investigation. Following the TAM-ChatGPT framework (Sallam et al., 2023), the study participants were recruited through convenience sampling, leveraging the professional networks of the author across different Universities in Nigeria. The recruitment process involved disseminating the survey link through targeted WhatsApp groups associated with students in various disciplines, including Management Sciences, Social Sciences, Sciences, Education, Arts, Schools of Medicine and Nursing across various HEIs in Nigeria. The survey enrollment period spanned from September 2023 to January 2024. Participation was voluntary, and no incentives were offered to the participants. The survey commenced with a comprehensive explanation of its objectives.

The questionnaire consists of two parts - section A and B. Section A comprises of 8 items which is the demographics (personal information) about the study participants, such as Gender, Institution, Type of University, academic level, faculty, awareness of ChatGPT, academic use of ChatGPT, and other use of ChatGPT with a maximum of score of 4. This is significant because it helps the researcher and other consumers of the research report or result to determine the respondents' degree of awareness, experience, and exposure to information, which is likely to provide a better understanding of the subject under investigation.

Section B consists of 31 items with seven subconstructs - Perceived usefulness, Perceived ease of use, Perceived risk, Personal Innovativeness, Social Influence, Behavioural Intention and Use Behaviour. This section discusses the most important part of the research (ChatGPT, learning, and research). The main constructs were recorded on a 4-point Likert scale, where 'Strongly Agree' was scored as 4, 'Agree' as 3, 'Disagree' as 2, and 'Strongly Disagree' as 1. For items indicating a negative attitude toward ChatGPT, the scoring was reversed.

The choice of a 4-point Likert scale is because at the inception of the questionnaire, participants were asked whether they had used ChatGPT or not. Hence, there was no need to include the “neutral scale in the main constructs, as it would serve no purpose therewith.

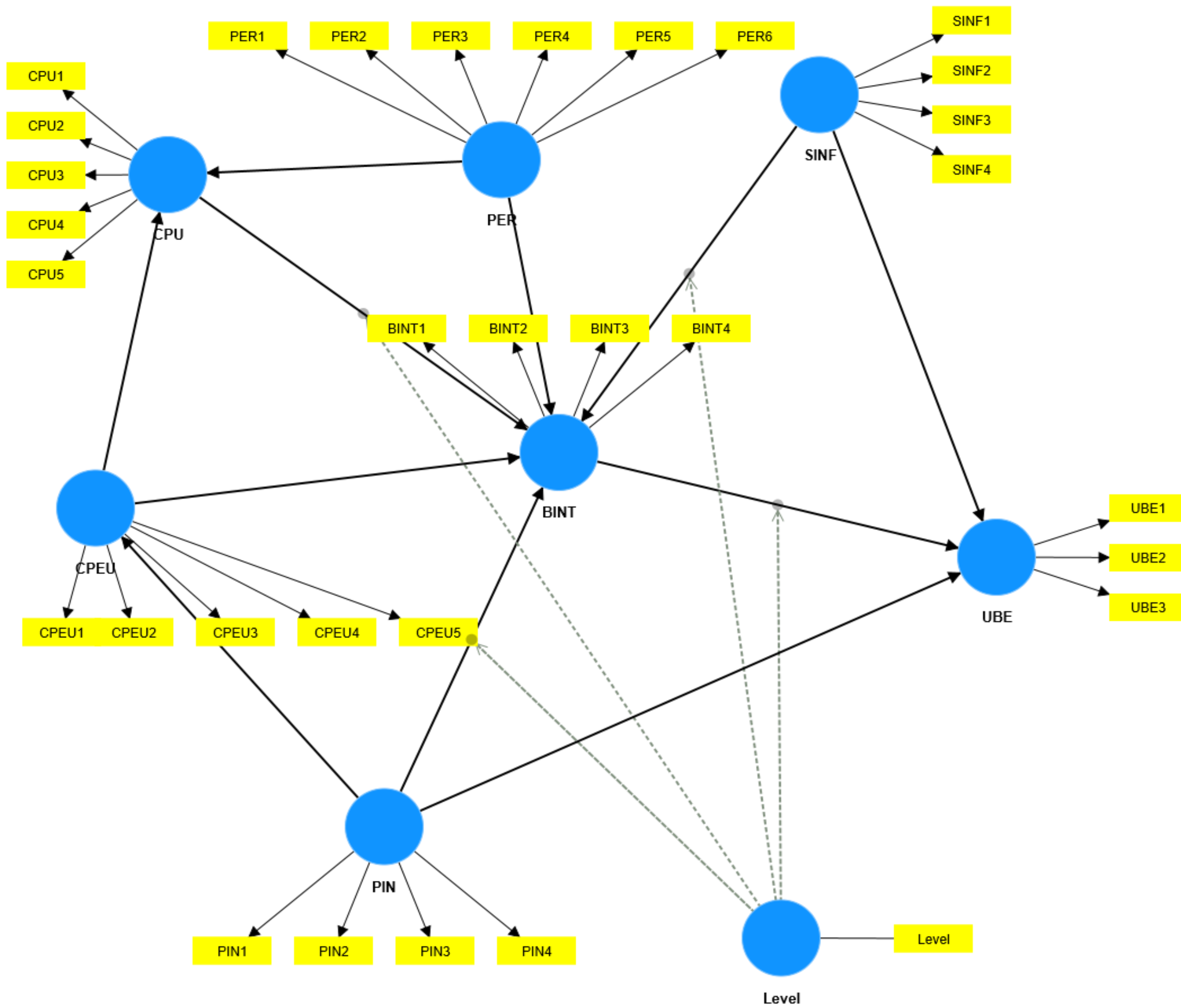

Figure 1: The research model

DATA ANALYSIS

The method used for data analysis was "partial least squares structural equation modelling" (PLS-SEM). PLS-SEM is really a versatile method that can be used in many different contexts, and compared to other modelling approaches, it requires a less conservative sample size and distribution criteria (Hair et al., 2019). The data from this investigation were analysed using the SmartPLS 4 programme (Ringle et al., 2022). We followed the instructions and carried out the data analysis in two stages (Anderson & Gerbing, 1988). Step one included evaluating the measurement model's internal consistency as well as its convergent and discriminant validities. We used the structural model in step two to confirm our hypothesis since the results from the previous stage were acceptable.

***Table 1:** Measurement scale and factor loadings*

Construct	Item	Items	Loading	Mean	St.dev.
ChatGPT Perceived Usefulness	CPU1	ChatGPT have make it easier for me to complete the assignments in university courses	0.813	3.478	0.639
	CPU2	ChatGPT-assisted assignments have increased my motivation to engage with coursework.	0.770	3.226	0.699
	CPU3	ChatGPT-assisted assignments have improved my understanding of course materials.	0.769	3.344	0.662
	CPU4	ChatGPT' have helped me to save time when searching for information	0.777	3.462	0.652
	CPU5	I found ChatGPT more useful in my studies than other sources of information that I have used previously	0.775	3.154	0.778
ChatGPT Perceived ease of use	CPEU1	It does not take long time to learn how to use ChatGPT	0.795	3.454	0.661
	CPEU2	ChatGPT does not require extensive technical knowledge	0.805	3.368	0.685
	CPEU3	Interaction process with ChatGPT is easy	0.868	3.419	0.643
	CPEU4	ChatGPT is easy to access	0.857	3.423	0.660
	CPEU5	ChatGPT saves users time	0.859	3.481	0.626
Perceived risk	PER1	I am concerned that ChatGPT might lead to plagiarism or academic dishonesty in my work.	0.642	2.988	0.840
	PER2	I worry that I might become too reliant on ChatGPT, potentially hindering my critical thinking skills.	0.769	2.979	0.861
	PER3	I'm cautious about how ChatGPT may affect the originality and authenticity of my research work.	0.805	3.064	0.753
	PER4	I fear that ChatGPT may provide inaccurate or unreliable information, posing a risk to the quality of my research.	0.696	2.794	0.857
	PER5	I am concerned about the potential security risks of using ChatGPT	0.813	2.900	0.833
	PER6	I'm mindful of the potential risk that ChatGPT could impact my ability to develop independent research skills	0.841	3.024	0.794
Perceived Innovativeness	PIN1	I like experimenting with new information technologies	0.790	3.501	0.612

	PIN2	If I heard about a new information technology, I would look for ways to experiment with it	0.819	3.367	0.627
	PIN3	Among my family/friends, I am usually the first to try out new information technologies	0.705	3.053	0.800
	PIN4	In general, I do not hesitate to try out new information technologies	0.844	3.360	0.686
Social Influence	SINF1	People who are important to me think I should use ChatGPT	0.841	2.902	0.883
	SINF2	People who influence my behavior believe that I should use ChatGPT	0.888	2.809	0.883
	SINF3	People whose opinions I value prefer me to use ChatGPT	0.895	2.796	0.874
	SINF4	I use ChatGPT based on social media recommendations	0.745	2.709	0.934
Behavioural Intention	BINT1	I will always try to use ChatGPT in my studies	0.850	3.056	0.707
	BINT2	I plan to continue to use ChatGPT frequently	0.873	3.037	0.714
	BINT3	I intend to continue using ChatGPT in the future	0.862	3.122	0.675
	BINT4	I predict I would use ChatGPT for my learning experiences	0.803	3.217	0.636
Use Behaviour	UBE1	I have used tools or techniques similar to ChatGPT to in the past	0.638	3.101	0.806
	UBE2	I spontaneously find myself using ChatGPT when I need information for my university assignments and duties	0.892	3.082	0.786
	UBE3	I often use ChatGPT as a source of information in my university assignments and duties	0.872	3.141	0.765

Source: *Researcher's PLS-SEM Computation, 2023*

Note: *The constructs were adapted from Validation of a Technology Acceptance Model-Based Scale (TAME-ChatGPT) on Health Students' Attitudes and Usage of ChatGPT in Jordan by Malik Sallam et al. DOI: https://doi.org/10.2196/preprints.48254*

Sample characteristics

Selecting an appropriate sample size is essential for Partial Least Squares Structural Equation Modelling (PLS-SEM) to guarantee the validity and accuracy of the results. The complexity of the model, the number of latent variables and indicators, the magnitudes of the effects, and the required degree of statistical power are some of the factors that affect the sample size in PLS-SEM investigations, which is not fixed (Hair et al., 2013). Some studies advocate a minimum sample size of 100 - 200 observations, while others suggest that the sample size to indicator ratio should be at least 5:1 or 10:1. (Kock, 2018). Because 31 markers were used in this investigation, a substantial sample size of 300 observations was possible.

From September 2023 to January 2024, the survey was disseminated using Google Forms whose link was sent to targeted WhatsApp groups associated with students across various HEI's in Nigeria. The duration of the survey was almost 5 months. With 268 valid replies in total, an 89.33% response rate was obtained. There were 154 male students (57.46%) and 114 female students (42.54%) in the sample. With 21 students from the first year (7.84%), 42 from the second year (15.67%), 51 from the third year (19.03%), 112 from the fourth year (41.79%), 27 from the fifth year (10.07%), and 15 from the sixth year (5.60%) of the bachelor's degree programme, the sample size was diverse in terms of academic progress.

RESULTS

With a maximum of 3000 iterations, default starting weights, and level as a weighting component, we used the PLS-SEM technique with the weighting route scheme in SmartPLS 4 software to estimate the model. The indicator loadings were used to analyse reflectively described constructs. An indicator loading over 0.7 indicated that the construct explained over 50% of the indicator's variance, demonstrating a satisfactory degree of item dependability.

Preliminary data analysis

Prior to beginning of the data analysis, the potential for multi-collinearity and common method bias (CMB) was examined. We employed the "variance inflation factor - VIF" to evaluate multi-collinearity. Every VIF value needs to be less than three (Hair et al., 2022). The VIFs ranged from 1.000 to 2.000, or no indication of multi-collinearity (see Table 2). Next, the presence of CMB was tested using Harman's single factor. Using the assessment by Podsakoff et al., (2003), the results demonstrated that loading every measurement item in the dataset at once produced a total variance of 44.678%, which is below the 50% threshold and suggests the absence of CMB.

***Table 2**: Multi-collinearity Assessment*

Construct	**BINT**	**CPEU**	**CPU**	**UBE**
BINT	-	-	-	1.888
CPEU	1.806	-	1.068	-
CPU	2.000	-	-	-
Level	1.067	-	-	1.037
PER	1.145	-	1.068	-
PIN	1.409	1.000	-	1.437
SINF	1.308	-	-	1.474

Source: *the researcher's Field Survey, 2023*

Measurement model

Prior to analysing the suggested hypotheses, the dependability and accuracy of the measuring items (indicators) and scales (constructs) were assessed (Hair et al., 2019). First, the loading of each indication was analysed. A loading above 0.708 indicates an adequate item loading. The data in Table 1 demonstrates that the loading of each item is higher than the acceptable amount, demonstrating that all items possess appropriate item dependability. Second, two metrics were utilised to examine the internal consistency: Cronbach's Alpha (α) and composite reliability (CR). The lowest acceptable value of α and CR is indicated to be 0.7 and should not exceed 0.95. This requirement is met by all structures (see Table 3), suggesting that internal consistency is present in all constructs. Third, the convergent validity was established by studying the "average variance extracted - AVE". The lowest acceptable AVE value is 0.5. As can be observed in Table 3, the AVE value of each construct is above 0.5, suggesting that convergent validity existed in all constructs. In addition, the examination of cross-loadings indicates that the items load heavily on their target constructions, demonstrating the presence of convergent validity.

Table 3: *Internal and convergent reliability and validity assessment*

Construct	Item	Loading	Cronbach's alpha (α)"	Composite reliability (rho_a)	Composite reliability (CR) (rho_c)	Average variance extracted (AVE)
ChatGPT Perceived Usefulness	CPU1	0.813	0.841	0.846	0.887	0.610
	CPU2	0.770				
	CPU3	0.769				
	CPU4	0.777				
	CPU5	0.775				
ChatGPT Perceived ease of use	CPEU1	0.795	0.894	0.902	0.921	0.702
	CPEU2	0.805				
	CPEU3	0.868				
	CPEU4	0.857				
	CPEU5	0.859				
Perceived risk	PER1	0.642	0.861	0.903	0.893	0.584
	PER2	0.769				
	PER3	0.805				
	PER4	0.696				
	PER5	0.813				
	PER6	0.841				
Perceived Innovativeness	PIN1	0.790	0.799	0.802	0.869	0.626
	PIN2	0.819				
	PIN3	0.705				
	PIN4	0.844				
Social Influence	SINF1	0.841	0.864	0.874	0.908	0.713
	SINF2	0.888				
	SINF3	0.895				
	SINF4	0.745				
Behavioural Intention	BINT1	0.850	0.869	0.874	0.910	0.718
	BINT2	0.873				
	BINT3	0.862				
	BINT4	0.803				
Use Behaviour	UBE1	0.638	0.726	0.764	0.848	0.655
	UBE2	0.892				
	UBE3	0.872				

Source: *Researcher's PLS-SEM Computation, 2023*

Structural model

The next stage is to evaluate the structural model after the receipt of an acceptable evaluation of the measurement model. First, the path coefficients (β) were evaluated for significance (see Table 6). The results show that the factors that are most important in enabling students' intentions to adopt ChatGPT are CPU (β = 0.344, p value < 0.000), CPEU (β = 0.618, p value < 0.00), SINF (β = 0.326, p value < 0.00), and PIN through UBE (β = 0.178, p value < 0.017).

As anticipated, BINT has a strong positive influence on PIN (β = 0.178, p value < 0.0017), SINF (β = 0.326, p value < 0.000), and CPEU (β = 0.618, p value < 0.000), making it a critical facilitator of these variables. CPU is a major driver of both PER and CPEU, as seen by the strong positive effects it had on PER (β = 0.028, p value < 0.598) and CPEU (β = 0.618, p value < 0.000). It was shown that PER had a negligible impact on BINT (β = -0.053, p value > 0.328), suggesting that PER is not a relevant factor in predicting students' BINT towards using ChatGPT. According to the proposal, PER is a major barrier to students' adoption of the metaverse and CPU, as seen by the strong negative impact it had on both BINT (β = -0.053, p value < 0.328) and CPU (β = 0.028, p value < 0.598).

The impacts of CPEU, CPU, and UBE on BINT produced R2 values of 0.53, 0.188, 0.392, and 0.503, respectively, as shown in Table 7. The predictive power (R2), means that these parameters together explained 53%, 18.8%, 39%, and 50% of the variation in BINT. It is acknowledged that such an explanatory ability is modest (Henseler et al., 2009). Table 8 also shows the outcomes of evaluating the prediction reliability (Q2). The findings suggest that the study model has sufficient predictive relevance since every dependent variable has a predictive relevance value that is significantly more than zero (Hair et al., 2019). When evaluating the impact size (f2), CPEU (0.212) created the largest effect size on BI, however PER (0.010) gave the largest effect size on CPU. Surprisingly, SINF had a significant impact on UBE (0.158).

At this stage, the discriminant validity evaluation was the last to be examined. A construct's correlation with no other construct may be less than its average variance extracted (AVE). The data in Table 4 offers proof that this need is met, indicating the existence of discriminant validity (Fornell & Larcker, 1981). In addition, the results of the "Heterotrait-Monotrait Ratio-HTMT" test show that all HTMT values are less than 0.85 (Henseler et al., 2015), which validates the findings based on the standards of Fornell & Larcker.

Table 4*: Fornell-Larcker criterion*

	BINT	CPEU	CPU	Level	PER	PIN	SINF	UBE
BINT	0.847							
CPEU	0.389	0.838						
CPU	0.588	0.625	0.781					
Level	-0.048	-0.019	0.069	1.000				
PER	0.167	0.252	0.184	-0.100	0.764			
PIN	0.530	0.434	0.443	0.126	0.263	0.791		
SINF	0.563	0.285	0.450	-0.034	0.202	0.295	0.844	
UBE	0.676	0.425	0.569	-0.026	0.238	0.484	0.491	0.809

Source: *Researcher's PLS-SEM Computation, 2023*

***Table 5**: Heterotrait-monotrait ratio (HTMT) - Discriminant validity*

	BINT	CPEU	CPU	Level	PER	PIN	SINF	UBE
BINT								
CPEU	0.440							
CPU	0.678	0.707						
Level	0.055	0.023	0.080					
PER	0.175	0.274	0.200	0.110				
PIN	0.635	0.508	0.540	0.142	0.300			
SINF	0.643	0.316	0.530	0.037	0.222	0.354		
UBE	0.840	0.522	0.713	0.028	0.289	0.621	0.631	

Source: *Researcher's PLS-SEM Computation, 2023*

***Table 6**: Hypotheses testing*

Hypothesis	Path	β	Mean	STDEV	T Statistics	Confidence interval	P Values	Assump-tion
H1	CPU -> BINT	0.344	0.345	0.060	5.720	(0.227, 0.463)	0.000	Yes
H2	CPEU -> CPU	0.618	0.614	0.051	12.087	(0.510, 0.709)	0.000	Yes
H3	PER -> CPU	0.028	0.038	0.053	0.527	(-0.065, 0.134)	0.598	No
H4	PER -> BINT	-0.053	-0.041	0.054	0.979	(-0.138, 0.082)	0.328	No
H5	PIN -> UBE	0.178	0.175	0.075	2.379	(0.243, 0.490)	0.017	Yes
H6	SINF -> BINT	0.326	0.330	0.056	5.867	(0.220, 0.436)	0.000	Yes

Source: *Researcher's PLS-SEM Computation, 2023*

***Table 7:** Assessment of predictive power and predictive relevance*

Construct	R-square	Assumption	R-square adjusted	Assumption
BINT	0.545	Moderate	0.529	Medium
CPEU	0.188	Moderate	0.185	Small
CPU	0.392	Moderate	0.387	Small
UBE	0.503	Moderate	0.493	Medium

Source: *Researcher's PLS-SEM Computation, 2023*

Table 8: *Effect Size Assessment*

Construct	BINT	CPU	UBE
CPEU	0.212	-	0.075
CPU	-	-	0.166
Level	-	-	-0.049
PER	0.010	-	-0.021
PIN	0.067	0.268	0.192
SINF	-	-	0.158

Source: *Researcher's PLS-SEM Computation, 2023*

Indirect effect assessment

The importance of the indirect effects of the components of the study model is demonstrated in Table 9. The findings suggest that certain indirect impacts were statistically significant, except for the indirect effect of some, which had a p-value greater than 0.05. Other factors exhibited a significant indirect impact with a p-value less than 0.05. This implies that the combination of CPEU and CPU might enhance students' inclination towards embracing the metaverse by enhancing their understanding of user behaviour experiences. In addition, the study found a significant negative indirect effect of PIN on BINT through UBE ($\beta = 0.160$, p value < 0.0000). This suggests that PIN does not directly cause a negative effect on BINT (as shown in Table 9), but it does have a detrimental impact on UBE by reducing CPU.

Table 9: *Indirect Effects Assessment*

Path	β	Mean	STDEV	t-Statistics	P-Values
PER -> CPU -> BINT	0.010	0.013	0.019	0.514	0.607*
PIN -> CPEU -> BINT	-0.025	-0.027	0.029	0.863	0.388*
PIN -> CPEU -> CPU	0.268	0.269	0.053	5.019	0.000
CPEU -> BINT -> UBE	-0.028	-0.030	0.033	0.844	0.399*
CPEU -> CPU -> BINT -> UBE	0.103	0.103	0.026	3.909	0.000
CPU -> BINT -> UBE	0.166	0.168	0.040	4.133	0.000
PER -> CPU -> BINT -> UBE	0.005	0.006	0.009	0.508	0.612*
PER -> BINT -> UBE	-0.026	-0.019	0.026	0.977	0.329*
PIN -> BINT -> UBE	0.160	0.161	0.044	3.615	0.000
PIN -> CPEU -> CPU -> BINT	0.092	0.093	0.024	3.769	0.000
SINF -> BINT -> UBE	0.158	0.160	0.036	4.362	0.000
PIN -> CPEU -> BINT -> UBE	-0.012	-0.013	0.015	0.817	0.414*
Level x CPU -> BINT -> UBE	-0.020	-0.020	0.028	0.708	0.479*
Level x PIN -> BINT -> UBE	0.019	0.018	0.032	0.576	0.564*
PIN -> CPEU -> CPU -> BINT -> UBE	0.045	0.045	0.015	3.016	0.003
CPEU -> CPU -> BINT	0.212	0.212	0.041	5.213	0.000

* Insignificant effect

DISCUSSION

The study examined the factors influencing Nigerian Higher Education students to adopt ChatGPT in learning. Drawing from existing literature, it is evident that the availability of ChatGPT and similar Large Language Models (LLM) technologies holds transformative societal implications, especially among undergraduate students. The inevitability of ChatGPT adoption, alongside other LLMs, is becoming increasingly apparent (Eysenbach, 2023). In addition, students have already started exploring innovative AI-based technology, considering the various advantages and disadvantages discussed in existing literature (Benoit, 2023).

The analysis of the structured questionnaire, PAUCLRQ, focused on investigating the Perception and Awareness of the use of ChatGPT in learning and research among university students in Nigeria. The study utilized a theoretical framework based on the Technology Acceptance Model (TAM) adapted for ChatGPT, and the data collected from 268 participants were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The sample consisted of students from various disciplines and academic levels across different universities in Nigeria. The diverse representation enhances the generalizability of the findings. The sample size of 268 participants was considered substantial for the PLS-SEM analysis, given the number of indicators used in the investigation.

The measurement scale, constructed with a 4-point Likert scale, demonstrated good reliability and validity. The internal consistency of the constructs was assessed through Cronbach's alpha and composite reliability, both of which exceeded the acceptable thresholds. The convergent validity was established using the average variance extracted (AVE), indicating that each construct had convergent validity.

The structural model analysis revealed significant relationships and insights into the factors influencing students' perception and adoption of ChatGPT in learning and research. The path coefficients (β) indicated the strength and direction of these relationships. The key findings are indicated below:

Perceived Usefulness (CPU) and Perceived Ease of Use (CPEU): Both CPU and CPEU had a significant positive impact on Behavioural Intention (BINT). This suggests that students who perceive ChatGPT as useful and easy to use are more likely to have the intention to adopt it for learning and research purposes.

Perceived Risk (PER): Surprisingly, perceived risk (PER) did not significantly influence students' Behavioural Intention (BINT). This finding contrasts with some prior literature, suggesting that perceived risk might not be a significant barrier to the adoption of ChatGPT in this context.

Personal Innovativeness (PIN): Personal innovativeness (PIN) had a positive impact on Use Behaviour (UBE) through Behavioural Intention (BINT). This suggests that more innovative students are more likely to use ChatGPT in their academic activities.

Social Influence (SINF): Social influence (SINF) positively influenced Behavioural Intention (BINT), indicating that the opinions and recommendations of others significantly impact students' intentions to adopt ChatGPT.

The R-squared values indicated that the model explained a moderate to small proportion of the variance in Behavioural Intention (BINT), Perceived Usefulness (CPU), Perceived Ease of Use (CPEU), and Use Behaviour (UBE). The effect size (f2) highlighted the significance of certain constructs, with CPEU having the largest effect size on BINT.

The analysis of indirect effects provided additional insights. The combination of CPU and CPEU was found to enhance students' inclination towards adopting ChatGPT, indicating a synergistic effect. However, the negative indirect effect of PIN on BINT through UBE suggests that personal innovativeness might hinder actual use behaviour by reducing the perceived usefulness of ChatGPT.

The study demonstrated discriminant validity, ensuring that each construct was more correlated with its own indicators than with indicators of other constructs. The Heterotrait-Monotrait Ratio (HTMT) further supported the discriminant validity assessment.

Meanwhile, the prominence of perceived usefulness as a significant construct shaping attitudes towards ChatGPT and its usage is understandable given the practical benefits it offers. It’s ability to generate accurate and relevant responses to user queries has revolutionised the way individuals interact with AI technology. Moreover, the convenience and efficiency it brings to various tasks, such as writing emails or drafting documents, have made it an indispensable tool for professionals and individuals alike. As a result, the perceived usefulness of ChatGPT has become a key determinant in shaping people's attitudes towards its adoption and usage (Lund & Wang, 2023; Aczel & Wagenmakers, 2023; Sanmarchi, Bucci & Golinelli, 2023).

Furthermore, the findings offer perceptive viewpoints on how the factors under investigation are related to one another. The results validate strong relationships between students' behavioural intention, perceptions of usefulness and ease of use, personal creativity, and learning and research. The study emphasizes how students' capacity to learn and conduct research can be significantly impacted by their perceptions of ChatGPT's perceived utility, perceived simplicity of use, personal inventiveness, and behavioural intention. Because using AI-generated content is so simple, students can become overly dependent on the program to write full essays, which could impede their ability to express themselves creatively and uniquely. This highlights how crucial it is to encourage students to use AI tools ethically and to develop their own innovative ideas (Kazi, et al., 2023).

This result is consistent with other research that suggests having favourable views about technology promotes the adoption of new innovations, but having negative or sceptical attitudes can obstruct acceptance (Lee & Lehto, 2013; Alfadda, & Mahdi, 2021). Therefore, providing thorough training and teaching on the technology is essential to promoting greater use of ChatGPT and other beneficial educational chatbots. Success in adoption hinges on highlighting the possible advantages and guaranteeing the accuracy of its results. Furthermore, publicly addressing any potential biases or limits and offering proof of the technology's accuracy and dependability can help allay worries about scepticism or lack of faith.

Limitations and Future Research

While the study provides valuable insights, it is essential to acknowledge its limitations. The data were collected through convenience sampling, limiting the generalizability of the findings. Additionally, the research focused on Nigerian Higher Institution students, and the results may not be fully applicable to other contexts. Future research could explore the perceptions and awareness of ChatGPT in diverse educational settings and cultures.

CONCLUSION

In conclusion, the findings of the study shed light on the factors influencing the adoption of ChatGPT in learning and research among university students in Nigeria. The significant positive impacts of perceived usefulness, perceived ease of use, personal innovativeness, and social influence highlight the importance of these factors in shaping students' intentions and behaviours regarding ChatGPT. The study contributes to the understanding of technology acceptance in the context of AI-driven tools like ChatGPT and provides valuable implications for educators, policymakers, and developers aiming to integrate such technologies into educational environments.

Finally, this study underscores the intricate dynamics influencing ChatGPT usage and emphasises the need for ethical AI tool usage, the promotion of individual creativity, and an understanding of the nuanced relationships between perceived usefulness and ease of use in educational settings. These findings lay the groundwork for further exploration and the development of informed strategies for the responsible integration of AI technologies in education.

Based on the findings, the study recommends the following:

- Clearly defined ethical rules for the use of AI tools in academic contexts should be developed and distributed, to provide educators and students with thorough instruction on how to use AI responsibly, including how to recognize and steer clear of plagiarism
- It should be stressed how crucial it is to strike a balance between upholding academic integrity and perceived usefulness. Instead of using artificial intelligence (AI) tools as quick fixes that degrade original thought, educators should advise students on how to use them as instruments for learning and creativity.
- Incorporate AI tools with instructional practices that support individual creativity and innovation. Instead of using technology to replace creative thinking, encourage students to embrace it as an enhancement.
- Include critical thinking exercises in the curriculum with a focus on assessing data produced by artificial intelligence systems. Urge students to evaluate the created content critically and to have a thorough comprehension of the subject matter.
- Explore interventions to align students' behavioural intentions with ethical and effective tool usage. Engage students in discussions about the responsible use of AI and its impact on their academic performance.
- Put monitoring systems in place to find instances of plagiarism made possible by AI. Provide students who might be having trouble navigating the ethical ramifications of using AI tools with support networks, such as counselling services.
- Acknowledge that social influences have a limited impact on research and learning and take personal reasons into account when implementing AI tools. Adjust instructional strategies to meet each student's needs and goals.

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