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Structural equation modeling of Nigerian science, technology and mathematics teachers' adoption of educational artificial intelligence tools

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ABSTRACT

Recent progress in artificial intelligence (AI) has aroused interest in the growth and development of educational AI tools (EAITs). Teachers' adoption of EAITs in classrooms has helped in shaping instructional decisions taken by them in an attempt to promote intelligently and actively students' meaningful learning of contents areas. Nevertheless, science, technology and mathematics (STM) teachers in Nigeria are rarely adopting and incorporating EAITs in their classrooms pedagogical discourse, and their perceptions of EAITs are rarely assessed. To this end, this study identified human factors in acceptance of EAITs by STM teachers in Nigeria. The study proposed an extended technology acceptance model (TAM) integrating STM teachers' perceived trust and instructional beliefs in EAITs through a quantitative blueprint of a descriptive survey design. The sample for the study consisted of 345 STM teachers in the six education districts of Lagos State, Nigeria. A valid and reliable instrument tagged adoption of educational artificial intelligence tools questionnaire (AEAITQ, α=0.87) was used to collect survey data which, were analysed via structural equation modeling. The study results showed that STM teachers with constructivist beliefs had the tendency to adopt and incorporate EAITs into their instructional decisions than their counterparts with traditional beliefs. Traditional instructional beliefs (TIB) had a negative influence on perceived trust (PT), perceived ease of use (PEOU), and perceived usefulness (PU). In addition, PT, PEOU and PU were strong factors predicting STM teachers' adoption of EAITs. However, PEOU was the strongest factor that predicted STM teachers' adoption of EAITs in pedagogical discourse. Important inferences regarding the growth and adoption of EAITs for significant stakeholders in STM education were discussed.

KEYWORDS: Structural equation modeling, Nigerian, science, technology and mathematics teachers, adoption, educational artificial intelligence tools.

1 INTRODUCTION

Modern improvement in engineering science has speeded up the evolution of artificial intelligence (AI) capabilities. Specifically, the speedy growth of deep and machine learning analytics has resulted into improved AI, promoting and making lives more meaningful due to the rapid effectiveness of various processes. The proliferation of higher education coupled with the enactment of particularized country-wide plan of action, has produced rapid growth of educational artificial intelligence (Asan, Bayrak & Choudhury, 2020). Afterwards, different types of educational artificial intelligence tools (EAITs) have been produced and used, in support of the major stakeholders in pedagogical milieus. In particular, AI chatbot has been used to support the learning of language (Jeon, 2022) with the intelligent tutoring systems (ITS) used to create individualized and machine-driven responses (Holstein, McLaren & Aleven, 2018). The far-flung adoption of EAITs has resulted into real pedagogical discourse that enhanced the conventional association between the students and the teachers (Guilherme, 2019).

The healthy cooperation between AI and people produces a mutual judgment that enhances an improved result than that created by either AI or people only (Zhang, Vera Liao & Bellamy, 2020). With the adoption of EAITs, teachers are bound to make intelligently far-reaching instructional judgments that would help students to take active roles in the learning process. Teacher-EAITs interaction can help in the analysis of learners' states of cognition (Troussas, Krouska & Virvou, 2020) and learning styles (Wei, Yang, Chen & Hu, 2018), predict academic performance of learners (Riestra-Gonz'alez, Paule-Ruiz & Ortin, 2021), and promote made-to-order erudition supported by learners' academic performance (Piech et al., 2015). Through interaction with EAITs, teachers can make comparison between materials enabled by EAIT and their own pedagogical decisions to make learners better students (S'anchez-Prieto, Cruz-Benito, Theron & Garcia-

Pealvo, 2020). Successful collaboration between teachers and machine intelligence has been found not only to increase students' learning (Holstein et al., 2018) but also that it helps teachers to have an unprejudiced view of their learners (Asan et al., 2020). More so, the implementation of EAITs in the classroom can help to minimise teachers' cognitive labour thereby providing them with more time to support and enhance students' learning.

In Nigeria and elsewhere, research suggests that STM teachers rarely incorporate EAITs in their pedagogical discourse in classrooms (Johal, Catellano, Tanaka, & Okita, 2018). More often, the relationship between STM teachers and EAITs needs to be better understood as this in-depth understanding seems very obscure (Song & Wang, 2020). The extant literature has shown that nurturing educational technology depends heavily on consumer's adoption and reception of the developed technology (Awofala & Oladipo, 2023; Pal & Patra, 2021). This has created a wave of research on teachers' conceptualisation of technologies (Awofala & Oladipo, 2023; Scherer, Siddiq & Tondeur, 2019). Thus, for attainment of success in the integration of EAITs in the classroom, it is expedient that effort is geared towards researching into factors that can promote or hinder STM teachers in adopting and incorporating EAITs into pedagogical discourse. Consequently, this study methodically investigated STM teachers' receptions of EAITs within the context of the technology acceptance model (TAM). TAM is a universal construct that explains users' intent and volition with respect to technology adoption (Davis, 1989). Two important factors explaining users' behavioural intention to adopt technology in the TAM are perceived ease of use and perceived usefulness of the technology. Behavioural intention refers to a user's likelihood or readiness to engage in a particular behavior, such as adopting a new technology (Awofala & Oladipo, 2023). Using TAM as a yardstick, extant studies have introduced extraneous factors to enable an all-inclusive description of technology integration in the classroom (Awofala & Oladipo, 2023; Girish, Kim, Sharma & Lee, 2021). With the EAITs, few studies (Choi & Ji, 2015; S'anchez-Prieto et al., 2019) have provided an extension of TAM to describe acceptance of AI-dependent appraisal among teachers. One of the studies only provided an abstract plan with no experimental confirmation (S'anchez-Prieto et al., 2019). The other study introduced teachers' perceived trust (PT) and instructional beliefs (IB) into the TAM within the context of EAITs (Choi, Jang, & Kim, 2023). While teachers' instructional beliefs are vital factors in EAITs integration in the classroom, researches have shown that they provide an explanation in teachers' reception of technology (Liu, Lin & Zhang, 2017). More so, research suggests that PT is a vital variable that explains teachers' behavioural intention to integrate AI-dependent tools in the classroom (Choi & Ji, 2015). The introduction of PT could help to unravel the incertitude and danger connected with AI assessment practices. Thus, PT is necessary in the present study to explain STM teachers' reception of EAITs. To the best of our knowledge, only few studies have incorporated PT and IB into the TAM to explain teachers' reception of EAITs and little is known about STM teachers' conceptualisation of adopting EAITs. In the present study, the planned theoretical framework was proved via structural equation modeling (SEM). It is our belief that the results of the present study would inform decisions regarding STM teachers' reception of EAITs in classroom discourse.

2 REVIEW OF RELATED LITERATURE

2.1 Technology Acceptance Model

The present study is anchored on an extended TAM. TAM is a universal model popular for explaining individuals' reception and acceptance of technologies (Davis, 1989). Perceived ease of use (PEOU) and perceived usefulness (PU) are two important variables in the TAM that are used to explain users' behavioural intention (BI) to use technologies (Awofala & Oladipo, 2023; Awofala, Oladipo, Akinoso, Arigbabu & Fatade, 2022). It is clear that technologies that are not only useful and convenient have the propensity to be adopted and accepted by the individuals (Awofala & Oladipo, 2023; Awofala et al., 2022). Numerous investigations have extended and modified the TAM by integrating external factors for a better and easy description of acceptance of technologies in various milieus. TAM has been modified and used to explain human factors affecting adoption of technologies in non-educational contexts to include AI-dependent products (Sohn & Kwon, 2020), autonomous vehicles (Choi & Ji, 2015), virtual reality (Sagnier, Loup-Escande, Lourdeaux, Thouvenin & Vallery, 2020) and in educational contexts to include virtual laboratories (Estriegana, Medina-Merodio & Barchino, 2019), video-dependent learning (Pal & Patra, 2021), ICT (Gurer & Akkaya, 2021), mobile devices (S'anchez-Prieto et al., 2019) and mobile library applications (Rafique, Almagrabi, Shamim, Anwar & Bashir, 2020). In the implementation of TAM, the PEOU and PU play a very important role in describing teachers' and students' behavioural intention to accepting technologies and their adoption and integration in education. In a study that relates TAM to perception of AI teaching assistants, Kim, Merrill, Xu and Sellnow (2020) showed that PEOU and PU were vital variables in the comprehension of AI teaching assistants acceptance and adoption in the classroom. However, few studies have shown teachers' acceptance and integration of EAITs in the classroom (Choi, Jang, & Kim, 2023; Nja, Idiege, Uwe et al., 2023; S'anchez-Prieto et al., 2020) thereby limiting our comprehension of how teachers perceived the adoption and integration of EAITs into classroom pedagogical discourse.

2.2 Instructional belief

The beliefs people hold are vital variables influencing their behaviours. Beliefs which are more cognitive nature influence and determine baviours, actual performance, intentions and attitudes towards an object (Awofala & Ojaleye, 2018). It is clear that teachers' beliefs have profound effect on their classroom behaviours and actions (Awofala, Lawani & Oraegbunam, 2020; Awofala & Sopekan, 2020; Sopekan & Awofala, 2019). Numerous studies have investigated the association between teachers' beliefs and their classroom behaviours (Gil-Flores, Rodriguez-Santero & Torres-Gordillo, 2017; Liu et al., 2017). Teachers' beliefs have been differentiated into self-efficacy beliefs (Akinsola & Awofala, 2009; Lano-Maduagu, Awofala, & Arigbabu, 2022), epistemological beliefs (Awofala et al., 2020) and instructional beliefs (Awofala, Lawani & Oraegbunam, 2019). The instructional beliefs could also be seen as a continuum describing teachers' perception of the processes of teaching and learning viewed as either students learning dependent on the teachers or learning constructed by the students with teachers serving to facilitate learning (Awofala et al., 2019). In this case, instructional beliefs are of two types namely traditional instructional belief (TIB) and constructivist instructional belief (CIB). The two beliefs are different: one is teacher dependent while the other is student dependent but both can be held simultaneously by the teacher. TIB is premised on behaviouristic psychology that promotes the conception of behavioural or behavior practices that are achievable via reinforcing stimulus or penalisation. CIB is premised on the psychology of constructivism that promotes students' active engagement and construction of knowledge for meaningful learning to take place. For teachers who exhibit TIB, they see students as passive recipient of knowledge and they are sages on the stages that possess absolute classroom authority that must be respected by the students and learning is based on teacher-directed activities (Awofala et al., 2019). Contrastingly, teachers who hold CIB see students as active participants in the classroom who engage in the construction of knowledge by socialising with others to achieve meaningful learning of instructional contents and activities (Awofala et al., 2019). Available research suggests that teachers' instructional beliefs have profound effects on how they integrate and utilise technologies in their classrooms (Tondeur, van Braak, Ertmer & Ottenbreit-Leftwich, 2017). In clear terms, it has been shown (Kim, Kim, Lee, Spector & DeMeester, 2013) that teachers with CIB oftentimes incorporate and use technology in their classroom discourses than teachers who exhibit TIB. In the same vein, it is reported that teachers who hold CIB tend to actively adopt and integrate digital technologies into their classroom discourses than teachers who hold TIB and whose activities are teacher-directed in the pedagogical discourses (Kim et al., 2013). Teachers who hold CIB oftentimes support the beneficial influence of technology as a learning tool than those who are strongly immersed in TIB (Choi et al., 2023; Tondeur et al., 2017). Some scholars have identified teachers' instructional beliefs has been important factors in TAM. In a survey of ICT usage of English teachers in China demonstrated through TAM, Liu et al. (2017) found that PEOU and PU of ICT were positively influenced by CIB while TIB showed no statistically significant influence on PU but on PEOU of ICT. A study on the perception of preservice mathematics teachers on ICT through TAM revealed that CIB had a statistically linear influence on PU and PEOU and an indirect influence on BI (Gurer & Akkaya, 2021). Contrastingly, PU was not significantly affected by TIB but TIB had a direct influence on PEOU (Gurer & Akkaya, 2021).

2.3 Perceived trust

Perceived Trust (PT) is described as a person's mental representation and awareness of the dependability and trustfulness of technology (Arpaci, 2016) and it is a vital variable that influence the decisions to integrate and incorporate new technology (Asan et al., 2020). With recourse to artificial intelligence, PT is regarded as very important because it connotes incertitude and danger. This quality of AI importantly influences individuals' PT, which yet resonates into a lower reception magnitude (Qin, Li & Yan, 2020; Asan et al., 2020). This difficulty arose as a result of the complex algorithm associated with AI, which inevitably affects how the AI reaches decisions and the deficiency of principle regarding their prognostication and prompting (Shin, 2021). Additionally, most AI that are machine learning-dependent require that data collected in the past be accurate and error free and this is important for the training of the AI model. Meanwhile, these data might not be free from input errors, unexplored defect, and prejudices that could lead to poor prognostication and prompting (Zhang et al., 2020) thereby affecting the accuracy of decisions for the AI. Remarkably, some investigations have introduced PT into TAM and their results showed that PT is an important factor in consumer mental representation and acceptance of new technology. The study by Gefen, Karahanna and Straub (2003) that involved users' perceptions of online shopping showed that PT was meaningfully related with both BI and PU, while PEOU was importantly related to PT. Additionally, in a study that involved mobile-based assessments, Nikou and Economides (2017) found that PT had a positive influence on PU. More so, in the analysis of people's reception of AI-based autonomous vehicles, Choi and Ji (2015) showed that PT had a significant positive effect on BI and PU. While numerous studies have been conducted showing the importance of PT in the relationship between humans and AI, few studies have been conducted emphasising teachers' PT with EAIT. In particular, studies about STM teachers' PT and EAIT are scarce (Choi et al., 2023). S'anchez-Prieto et al. (2019) provided an extension of TAM through incorporation of PT to describe acceptance of AI-dependent appraisal among teachers. This study only provided an abstract plan with no experimental confirmation. Investigating the acceptance and trust in AI-based educational technology is crucial for several reasons: When users trust and accept a technology, they are more likely to use it consistently and effectively, leading to better educational outcomes. Trust fosters a positive attitude towards the technology, increasing willingness to engage with it and explore its full potential. Students and educators who trust AI tools are more likely to integrate them into their learning and teaching processes, leveraging their full capabilities to enhance learning outcomes. Trust in adaptive learning technologies can lead to more personalized learning experiences, addressing individual student needs more effectively. Investigating trust and acceptance helps identify potential biases and ethical concerns, ensuring that the technology is used in a fair and responsible manner. Understanding trust dynamics promotes the development of transparent and accountable AI systems, which are crucial for ethical use. Technologies that are trusted and accepted are more likely to be integrated into educational systems in the long term, ensuring sustained impact. Higher acceptance can lead to increased support from stakeholders, including funding bodies, policy makers, and educational institutions. Trust in AI technology enhances user confidence, reducing anxiety and resistance to new tools. When students and educators feel comfortable with the technology, it contributes to a positive learning environment and overall well-being. Trust in AI can lead to the adoption of innovative teaching and learning practices, fostering creativity and critical thinking. Acceptance of AI tools can facilitate collaborative learning environments, where students and teachers can work together more effectively. Trustworthy AI tools provide reliable data and insights, aiding educators in making informed decisions about curriculum design, student support, and resource allocation. Acceptance of AI enables continuous feedback loops, helping educators and developers refine and improve the technology. Educational institutions that successfully implement and integrate trusted AI technologies can gain a competitive edge, attracting students and faculty. Preparing students for a future where AI is ubiquitous requires integrating AI technologies into education in a way that is trusted and accepted.

3 METHODOLOGY

3.1 Research questions and hypotheses `

The goal of the present study was to methodically investigate STM teachers' mental representation of the acceptance of EAITs. Particularly, three research questions were set for achieving the goal of the research.
Research Question One: What is the influence of STM teachers' pedagogical belief on their acceptance of EAITs?
Research Question Two: What is the influence of STM teachers' perceived trust on their acceptance of EAITs?
Research Question Three: Among the variables of the study what is the most important predictor of STM teachers' behavioural intention to use EAITs?

The present study provided an empirical framework in line with the extant literature by extending TAM to incorporate instructional beliefs and perceived trust. The projected conceptual model and the associated research hypotheses are depicted in Figure 1.

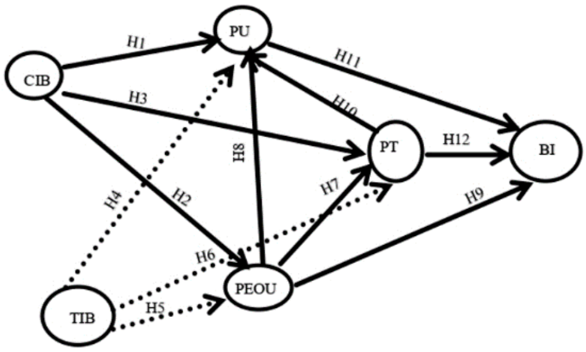

Figure 1. Research model
H1: CIB has a positive effect on PU of EAITs.
H2: CIB has a positive effect on PEOU of EAITs
H3: CIB has a positive effect on PT of EAITs
H4: TIB has a negative effect on PU of EAITs
H5: TIB has a negative effect on PEOU of EAITs
H6: TIB has a negative effect on PT of EAITs
H7: PEOU has a positive effect on PT of EAITs
H8: PEOU has a positive effect on PU of EAITs
H9: PEOU has a positive effect on BI to use EAITs.
H10: PT has a positive effect on PU of EAITs
H11: PU has a positive effect on BI to use EAITs.
H12: PT has a positive effect on BI to use EAITs

3.2 Research Design

The study adopted a quantitative blueprint of a descriptive survey design.

3.2.1. Participants

A request was made to the STM teachers attending an annual conference in Lagos State, Nigeria to report their BI, PT, PU, PEOU and instructional beliefs via a paper and pencil questionnaire. The STM teachers were duly informed about the purpose of the study and informed consent forms were distributed prior to the time of data collection. All the 345 STM teachers concurred to using their information for research purposes only. The 345 STM teachers could be segregated into 67.8% of males and 32.2% of females. Their ages ranged from 25 years to 64 years with a mean age of 45 years and (SD=7.1 years). The age and gender of the participants were not considered further in this study and so they have no impact on the research process except for descriptive purposes.

3.2.2. Instruments

A paper and pencil questionnaire was implemented in this study. The instrument was tagged adoption of educational artificial intelligence tools questionnaire (AEAITQ). The 24 items of the AEAITQ were adapted from the extant literature (Chan & Elliott, 2004; Liu et al., 2017; Choi & Ji, 2015; Nikou & Economides, 2017; Venkatesh & Bala, 2008) to ensure reliability and validity and the items were modified to conform with the intent of the study. A 5-point Likert scale was used for all items of the questionnaire with 5 denoting "strongly agree" and 1 denoting "strongly disagree." The questionnaire contained two sections. Section one contained biographical information of the participants including, age and gender. Section two contained items that were found reliable and depicted BI (4 items; α=0.86), PT (4 items; α=0.88), PU (4 items; α=0.92), PEOU (4 items; α=0.90) and instructional beliefs (8 items; α=0.89) of STM teachers. In general, the AEAITQ has a reliability coefficient of α=0.87. All the reliability coefficients were determined in the present study. The average completion time for the questionnaire was 20 minutes. The questionnaire was correctly filled by the STM teachers as there were no missing data.

3.2.3. Data analysis

The research model was tested using the structural equation modeling (SEM) and analysed through maximum likelihood estimation with the AMOS 26 software. The two-step SEM procedure recommended by Anderson and Gerbing (1988) was enacted in the study. Step one assessed the measurement model in order to confirm the model validity and reliability. Step two involved the assessment of the structural model in order to test the research hypotheses. Additionally, path analyses were carried out in order to assess the total effects, indirect effects and direct effects of all the variables as supported by previous studies (Choi et al., 2023; Gurer & Akkaya, 2021; Lee et al., 2019; Rafique et al., 2020; Wallace & Sheetz, 2014).

Variable	mean	Stand Dev	Skewness	Kurtosis
BI	3.705	0.457	-0.773	0.664
PT	3.693	0.767	-0.368	-0.193
PU	3.853	0.622	-0.434	-0.038
PEOU	3.456	0.921	-0.058	-0.092
TIB	3.224	0.942	0.541	-0.093
CIB	4.625	0.662	-0.663	-0.216

Table 1. Descriptive Statistics and Skewness and Kurtosis
Note: BI= Behavioral Intention; PT=Perceived Trust; PU=Perceived Usefulness; PEOU=Perceived Ease of Use; TIB=Traditional Instructional Beliefs; CIB=Constructivist Instructional Beliefs

4 RESULTS

4.1 Descriptive statistics and normality

Table 1 showed the mean, standard deviation, skewness and kurtosis of all the variables of the study. The STM teachers' mean scores for TIB and CIB were 3.224 and 4.625, respectively, showing that the STM teachers in the present study were more inclined towards constructivist instructional beliefs. At the same time STM teachers in this study seem to hold both traditional and constructivist beliefs simultaneously. As shown in Table 1 the mean scores for BI, PT, PU and PEOU were all above 3.0 and this showed that the STM teachers in the present study exhibited positive mental representation of the EAITs. In this study, the normality of the variables was assessed in order to prevent a contorted computation. As contained in Table 1, the absolute values of kurtosis and skewness of the six variables of the study were within acceptable range of not greater than eight and three, respectively (Kline, 2015).

4.2 Measurement model analysis

To verify the measurement model and to evaluate the discriminant and convergent validity and assess reliability the confirmatory factor analysis (CFA) was adopted (Hair, Hult, Ringle & Sarstedt, 2021). Average variance extracted (AVE) was used in assessing the convergent validity while reliability was investigated using Cronbach alpha and composite reliability (CR). Additionally, discriminant validity was assessed using Fornell and Larcker criterion (Fornell & Larcker, 1981). Tables 2 and 3 contained these numerical values. The adequacy of each item reliability was ensured with factor loading values above 0.7 (Hair et al., 2021). As contained in Table 2, the AVE values were higher than the threshold value of 0.5 (Hair et al., 2021) with values ranging from 0.608 to 0.858 showing satisfactory convergent validity. The CR values ranged from 0.855 to 0.948 while the Cronbach alpha values ranged from 0.852 to 0.944 and these values were greater than the suggested threshold of 0.7 (Hair et al., 2021) meaning that the measures have satisfactory construct reliability. According to Fornell and Larcker (1981), for appropriate discriminant validity, the square root of the AVE for each latent variable needs to be greater than its corresponding correlation coefficients between the other variables. Table 3 revealed that the study model has satisfactory discriminant validity.

Variable	Item	loading	CR	AVE	Cronbach α
BI	B11	0.953	0.924	0.746	0.922
	B12	0.945			
	B13	0.972			
	B14	0.924			
PT	PT1	0.967	0.961	0.757	0.960
	PT2	0.928			
	PT3	0.919			

	PT4	0.931			
PU	PU1	0.891	0.877	0.671	0.874
	PU2	0.927			
	PU3	0.936			
	PU4	0.896			
PEOU	PEOU1	0.929	0.856	0.638	0.854
	PEOU2	0.917			
	PEOU3	0.981			
	PEOU4	0.891			
TIB	TIB1	0.821	0.917	0.739	0.914
	TIB2	0.834			
	TIB3	0.817			
	TIB4	0.762			
CIB	CIB1	0.910	0.813	0.624	0.809
	CIB2	0.819			
	CIB3	0.816			
	CIB4	0.921			

Table 2. Construct reliability and convergent validity

4.3 Structural model analysis

Table 4 showed the important model fit indexes considered in the study in order to verify the structural model. Notable among the fit indexes include root mean square error of approximation (RMSEA), Tucker Lewis index (TLI), comparative fit index (CFI), normed fit index (NFI), and the ratio of chi-square to its degree of freedom (x 2 /df). All these were assessed in order to ensure that the proposed model is acceptable. The values of the fit indexes were in accordance with the suggested standard (Hair et al., 2021; Kline, 2015) as seen in the Table 4 thereby showing a good model fit.

Variables	PT	TIB	PU	PEOU	CIB	BI
PT	0.815					
TIB	-0.462	0.763				
PU	0.517	-0.423	0.817			
PEOU	0.654	-0.378	0.657	0.938		
CIB	0.528	0.458	0.459	0.542	0.873	
BI	0.671	0.348	0.782	0.542	0.528	0.894

Table 3. Discriminant validity and correlation matrix

RMSEA= 0.072, TLI =0.982, CFI =0.967, NFI =0.942, x2/df =3.467. While Table 5 showed the outcomes for the predictive power (R2) of the research model, Figure 2 showed the path coefficient estimates and their significance for assessing causal associations. In the present study, STM teachers' BI to use EAITs was predicted by PU, PT, and PEOU with 88.8% (R2=0.888). Additionally, STM teachers' PT in EAITs was predicted by PEOU, TIB, and CIB accounting for 62.3% (R2=0.623). STM teachers' PEOU in EAITs was predicted by TIB and CIB accounting for 24.5% (R2=0.245). STM teachers' PU in EAITs was predicted by PT, PEOU, TIB, and CIB accounting for 72.5% (R2=0.725).

Fit indices	Recommended value	Study value
RMSEA	<0.08	0.072

TLI	>0.9	0.982
CFI	>0.9	0.967
NFI	>0.9	0.942
x 2 /df	<5.0	3.467

Table 4. Proposed model Fit indices

All the 12 hypotheses were fully supported in this study. CIB had a positive influence on PU (b =0.302, p<0.01), PEOU (b=0.461, p<0.001), and PT (b=0.217, p<0.05) supportive of H1, H2 and H3 respectively. Additionally, TIB had a negative influence on PU (b = -0.234, p<0.05), PEOU (b=0.217, p<0.05), and PT (b=0.202, p<0.05) satisfying H4, H5 and H6 respectively. Moreover, hypotheses H7 to H12 that were associated with PT and TAM factors were all satisfied in this study. PEOU had a significant positive effect on PT (b=0.674, p<0.001), PU (b=0.389, p<0.001) and BI (b=0.329, p<0.001). PT had a significant positive influence on PU (b=0.506, p< 0.001). PU had a significant positive influence on BI (b= 0.629, p<0.001). Lastly, PT had a significant positive influence on BI (b=0.203, p<0.05).

Hypotheses	Path	b coefficients	S.E	t-value	Outcomes
H1	CIB→PU	0.302	0.122	3.571	Supported
H2	CIB→PEOU	0.461	0.222	4.016	Supported
H3	CIB→PT	0.217	0.202	3.514	Supported
H4	TIB→PU	-0.234	0.141	-2.909	Supported
H5	TIB→PEOU	-0.217	0.178	-3.123	Supported
H6	TIB→PT	-0.202	0.158	-2.763	Supported
H7	PEOU→PT	0.674	0.179	7.772	Supported
H8	PEOU→PU	0.389	0.152	3.565	Supported
H9	PEOU→BI	0.329	0.146	4.211	Supported
H10	PT→PU	0.506	0.139	7.233	Supported
H11	PU→BI	0.629	0.187	8.504	Supported
H12	PT→BI	0.203	0.157	3.268	Supported

Table 5. Structural model outcomes

Table 6 showed the results of the path analysis that describe the total effects, direct and indirect effects of the six constructs of the study. The most predominant meaningful factors of STM teachers' BI to use EAITs were PEOU (b = 0.830), followed by PU (b=0.612), CIB (b=0.391), PT (b=0.343), and TIB (b=0.339). Additionally, PU had the highest direct influence on BI (b = 0.612), whereas CIB had the highest indirect influence on BI (b= 0.391). More so, the total effect sizes of PEOU and CIB on STM teachers' PT were b= 0.681 and b=0.530, respectively showing that they were important factors in PT. PEOU and CIB were the strong factors in PU with a total effect size of b = 0.702, and b = 0.491, followed by PT (b = 0.307) and TIB (b =0.167). However, CIB (b = 0.402) showed a higher impact on PEOU than TIB (b = -0.213).

Dependent variable	Independent variable	Standardized estimates		
		direct	indirect	total
PEOU (R^2=0.245)	CIB	0.402	-	0.402
	TIB	-0.213	-	-0.213

PU (R^2=0.725)	CIB	0.345	0.146	0.491
	TIB	-0.167	0.334	0.167
	PEOU	0.388	0.314	0.702
	PT	0.307	-	0.307
PT (R^2=0.623)	CIB	0.214	0.316	0.530
	TIB	-0.182	0.204	0.022
	PEOU	0.681	-	0.681
BI (R^2=0.888)	CIB	-	0.391	0.391
	TIB	-	0.339	0.339
	PEOU	0.411	0.419	0.830
	PT	0.211	0.132	0.343
	PU	0.612	-	0.612

Table 6. Model direct, indirect and total effects

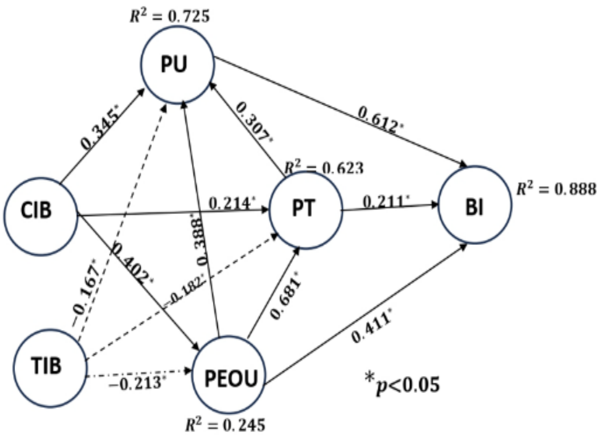

Figure 2. Path coefficient estimates

5 DISCUSSION

5.1 Adoption of EAIT and Instructional beliefs

RQ1 examines the influence of STM teachers' pedagogical belief on reception of EAITs. The outcomes revealed that CIB had a direct positive effect on PU (H1) and PEOU (H2), in addition to having an indirect effect on BI. This outcome agrees with prior investigations that centred on educators' instructional beliefs and their conceptualization of ICT for instructional intents (Liu et al., 2017). Clearly, educators that are constructivist inclined are more likely to conceptualise EAITs as easier to manipulate and usable (Choi et al., 2023). Prospective teachers' CIB has a positive impact on PU and PEOU, thus reinforcing their readiness to enact and use ICT in education during pedagogical discourse (Gurer & Akkaya, 2021).

In the present study, STM teachers have the tendency to adopt EAITs when they are inclined to be more constructivist. CIB is a striking factor for anticipating STM teachers' intentions to use EAITs. Nevertheless, TIB showed a significant direct negative effect on PU (H4) and PEOU (H5) and indirect positive effect on BI. These outcomes sufficiently supported the hypotheses raised in the present study, in which TIB is predicted to have a negative influence on STM teachers' PU, PEOU and BI to adopt EAITs. These outcomes do not corroborate the findings that TIB had a positive effect on PEOU and a non-significant influence on PU (Gurer & Akkaya, 2021; Liu et al., 2017). These anticipated results are premised on two dominant factors. First, majority of the participants in this study held both beliefs (CIB and TIB) simultaneously (Choi et al., 2023) even though some participants were more constructivist oriented than the others. The parity in the scores of CIB and TIB shows that participants were both constructivist and traditionalist oriented. The high level of respondents' TIB scores could have explained the negative effect of perception on EAITs. Second, the milieu in which the study was conducted may have had an impact.

The study was carried out in Nigeria and specifically in Lagos State. Although, numerous workshops had been conducted for STM teachers in Lagos State to make them more constructivist oriented, it seems those workshops had little effect on them as some of them still clinch to the traditional pedagogical orientation. EAIT is a new innovation in Nigeria and teachers are generally being trained on its adoption in schools. Traditional educational beliefs had a negative impact on perceived trust, perceived ease of use, and perceived usefulness of new technologies for several reasons: Long-standing reliance on traditional methods fosters skepticism towards new technologies. Therefore, educators may doubt the reliability and effectiveness of AI-based tools, questioning their ability to deliver consistent and accurate results. Traditional approaches often involve familiar, well-understood processes. A lack of understanding about how AI systems work can lead to mistrust, as educators may feel uncertain about the decision-making processes of these technologies. Traditional educators might fear that AI and new technologies could replace their roles. This fear can lead to resistance and a lack of trust in these tools, as educators might view them as a threat rather than a complement to their teaching. Familiarity with traditional teaching methods creates comfort and ease in their application. Transitioning to new technologies requires learning new skills and processes, which can be perceived as difficult and time-consuming. Traditional methods are often straightforward and require minimal technological proficiency. AI-based tools can be perceived as complex and daunting, especially for educators with limited tech experience, leading to a belief that they are not easy to use.

The present study showed that while CIB had a positive impact on PT (H3), TIB had a negative influence on PT (H6). These outcomes reveal that constructivist teachers tend to perceive EAITs as trustworthy whereas teachers that are traditionalist tend not to see EAITs as trustworthy. Presently, only one study had identified the relationship between instructional beliefs and perceived trust (Choi et al., 2023) in which CIB had a positive influence on PT whereas TIB had no influence on PT. Research suggests that comfortability with using mobile devices reduces the phobia associated with the technology use (Chiu & Churchill, 2016) and users' technophobia influences their trust in technology (Hwang & Kim, 2007). Thus, it can be deduced that teachers who are constructivist oriented tend to embrace new technology, which more often than not may lead to low level of anxiety whereas teachers with traditionalist orientation tend to shun or avoid new technology which may lead to higher level of anxiety.

The present study has underscored the importance of comprehending STM teachers' instructional beliefs in order to enhance their acceptance of EAITs. Clearly, STM teachers rarely integrate EAITs, although successful adoption and collaboration with EAITs help them to optimise pedagogical success needed to create optimal and meaningful learning (Nye, 2014). It is high time STM teachers in Nigeria migrated from traditional orientation to constructivist orientation in order to optimise effective and efficient use of new technology. Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur and Sendurur (2012) noted that for teachers to successfully integrate new technology, their change from TIB to CIB is pertinent and sufficiently necessary. More opportunities should be given to STM teachers to integrate EAITs into their instructional discourse in a more proactive, purposeful, and progressive way. Research suggests that teachers who are traditionally oriented tend to use technology in a more traditional way (Ertmer et al., 2012) and for simple tasks (Fraillon, Ainley, Schulz, Friedman & Gebhardt, 2014) thereby harming student-centred learning processes (Liu et al., 2017). Traditional teachers may have a greater inclination towards traditional methods for several reasons: Many teachers have been trained and have built their careers using traditional teaching methods. These methods are familiar and comfortable, reducing the perceived risk associated with change. Teachers may believe that traditional methods, such as direct instruction and standardized assessments, are effective because they have seen positive results over time. The adoption of new technologies and methodologies requires stepping into unfamiliar territory, which can be intimidating. Teachers might worry about their ability to effectively use new tools. Integrating new technologies often requires additional training and preparation time. Teachers, who are often already burdened with heavy workloads, may be reluctant to invest the extra effort required to learn and implement new systems. Teachers may not receive adequate training on how to effectively use new technologies and integrate them into their teaching practices. Teachers may be skeptical about whether new technologies will actually improve student learning outcomes. They may worry that the focus on technology could detract from essential skills like critical thinking and interpersonal communication.

To sustain optimum instructional benefit from EAITs, STM teachers, most especially those that hold traditional beliefs should be given the chance to proactively utilise EAITs for more robust and complex tasks to enhance meaningful learning. AI educational tools can be used for more complex and robust tasks through creating personalized learning paths based on individual student performance, learning styles, and preferences. With this, students receive customized content and exercises that adapt to their needs, ensuring they are neither bored with too-easy material nor overwhelmed by too-difficult challenges. Develop AI-driven tutoring systems that can engage students in complex problem-solving tasks, providing hints, feedback, and step-by-step guidance. This helps students learn to tackle challenging problems with personalized support, which promotes deeper understanding and retention. Use AI to facilitate collaborative projects and peer learning by forming balanced groups based on students' strengths and weaknesses, and monitoring interactions to provide real-time feedback. This helps students benefit from diverse perspectives and collaborative problem-solving, which enhances critical thinking and communication skills. Integrate AI with virtual reality (VR) and augmented reality (AR) to create immersive, interactive learning experiences that simulate real-world scenarios. With this, students can engage in hands-on learning in safe, controlled environments, enhancing understanding and application of complex concepts.

5.2 Adoption of EAITs and Perceived trust

RQ2 examines the influence of STM teachers' perceived trust on their reception of EAITs. The outcomes showed that PT had a direct positive impact on PU (H9) and BI (H11) while it received a direct positive effect from PEOU (H8). These outcomes are in tandem with the results of researchers (Choi & Ji, 2015; Gefen et al., 2003; Nikou & Economides, 2017) who have confirmed that PT had a significant impact on PU and BI, whereas PEOU significantly impacted PT. The outcomes from RQ2 show that STM teachers' PT in EAITs is a conspicuous factor for anticipating their intents to utilise EAITs as this could promote the building of trustworthiness of EAITs to enhance STM teachers' acceptance. It is clear that STM teachers' PT in EAITs can be elevated by enhancing the performance of EAITs (Bitkina et al., 2020) and also providing performance information on EAITs (Yin, Vaughan & Wallach, 2019). This can promote efficient enactment of EAITs during pedagogical discourse. Ensuring the transparency of EAITs is another way for elevating teachers' PT in EAITs. Choi and Ji (2015) noted that opacity and clarity is valuable in explaining users' PT. Nevertheless, the quality of decisions put forward by AI may sometimes not be secured. Additionally, most AI is connected with complex algorithms that are difficult to dissect how outcomes are reached thereby promoting incomprehensibility. Shin (2021) noted that Explainable AI (XAI) is a powerful way of ensuring AI accountability and transparency. Explainable AI (XAI) refers to artificial intelligence systems designed to make their decision-making processes understandable to humans. XAI promotes transparency in artificial intelligence by providing insights into how specific inputs influence the output, allowing users to comprehend the decision-making process. XAI systems offer clear explanations of how they operate, the data they use, and the steps taken to reach conclusions. XAI enables stakeholders to hold AI systems and their creators accountable for the outcomes produced. As reported by Rai (2020), XAI provides clarity on how an AI makes predictions and decisions. The value of XAI in high-risk milieus like healthcare, law enforcement and finance has been a source of debate (Pawar, O'Shea, Rea, & O'Reilly, 2020). From this vantage position, the implementation of EAITs using XAI could be of benefit to STM teachers who need to comprehend the importance of materials produced by EAITs. With this information, transparency is enhanced and STM teachers are helped in determining the instructional actions they will enact in the classrooms. Lastly, building STM teachers' perceived trust in EAITs can be achieved via user-friendly interfaces. The present study showed that PEOU was the most powerful predictor of PT. Thus, it can be deduced that when STM teachers find it convenient to use EAITs, they are more likely to have more trust in them.

5.3 Predictors of behavioral intention to utilise the EAITs

RQ3 examined the most important predictor of STM teachers' behavioural intention to use EAITs. Consequently, in this study, hypotheses that deal with the associations among TAM variables were investigated. The outcomes showed that all three hypotheses connected with TAM variables were fully supported. This confirmed the potency of relying on TAM in explaining STM teachers' adoption of EAITs. The study established that PEOU (H10) and PU (H12) were two significant positive predictors of BI. This result is in agreement with prior studies that confirmed that PEOU and PU are major determinants of BI (Kim et al., 2020; Wallace & Sheetz, 2014). Studies have shown that teachers are more likely to adopt ICT in education if they perceive it to be useful and easy to operate (Akar, 2019;) and that PEOU and PU are key determinants of preservice mathematics teachers' intentions to use ICT applications (Gurer & Akkaya, 2021). Thus, EAITs should be developed in a way that will ensure their operational efficiency and usefulness during instructional discourse in the classroom. Clearly, in the present study, PEOU of STM teachers had a significant influence on PU (H7). This result is analogous to prior findings that showcased the efficacy of PEOU in determining PU (Gurer & Akkaya, 2021; Liu et al., 2017). The implication of this finding is that STM teachers are likely to benefit more from EAITs if they realise that their use is handy and commodious. In the present study, PEOU was the most important predictor of STM teachers' behavioural intention to use EAITs. The implication of this is that developing easily operated EAITs for STM teachers should be a top priority when encouraging STM teachers to adopt EAITs. This finding disagrees with prior studies that reported PU as the key determinant of BI, which implied that teachers' intentions are heavily dependent on the usefulness of the technology rather than its convenience (Akar, 2019; Alexandrakis, Chorianopoulos & Tselios, 2020). This conflicting result stemmed from the high relationship between STM teachers' PEU and PT. Presently, in this study, STM teachers' PEOU was a key variable that impacted PT, and this may have led to PEOU to be the most powerful predictor of behavioural intentions to use EAITs. Additionally, Mercader and Gair'ın (2020) noted that teachers who lack experience and are incompetent in using digital technology usually show resistance in the integration of instructional technologies into their pedagogical discourse in the classrooms. Because EAITs are new innovations, time spent on workshops and training for STM teachers to raise their experience and competency in using EAITs efficiently may have been insufficient. This may have caused PEOU to be the most important predictor of BI. Adopting EAITs in instructional milieu may rely on factors that strengthen teachers' acceptance and improvement of technology. Thus, it is important for EAIT developers to design EAITs in a simple and handy mode so that technical obstacles are removed to ensure that they are easy to use with minimal mental load. EAITs should be lucid, accessible and comprehensible to all users. In addition, schools should institute training programmes for STM teachers that provide effective ways of utilising EAITs in instructional discourse in the classrooms.

The perceived trust, perceived ease of use, and perceived usefulness are powerful factors in predicting the acceptance of AI tools in the present study for several reasons: If users trust an AI tool, they are more likely to use it consistently and rely on its outputs. Trust mitigates concerns about errors or unexpected behavior, which is especially important in sensitive areas like education. Users are more likely to adopt AI tools if they believe their personal information and that of their students is secure, reducing fear of data breaches or misuse. Transparency in AI processes helps users feel more in control and confident about integrating the technology into their routines. Tools that are easy to use require less effort to learn and integrate into daily practices, which encourages adoption. Educators, often pressed for time, are more likely to adopt tools that streamline their work rather than add complexity. A positive user experience leads to greater satisfaction and a higher likelihood of continued use. If a tool is perceived as complicated or frustrating, users are less likely to invest the time needed to use it effectively. When users feel supported and capable of using a tool, their confidence in its ease of use increases, leading to higher acceptance rates. If educators perceive an AI tool as useful, they believe it will enhance their teaching, improve student outcomes, or make administrative tasks easier. This relevance to their goals drives adoption. Demonstrable benefits, such as better student engagement, personalized learning experiences, or streamlined grading processes, make the tool more attractive to users. AI tools that offer sustainable advantages, such as ongoing improvements in learning outcomes or data-driven insights, are more likely to be adopted as users see their value over time.

6 CONCLUSIONS

Recent progress in artificial intelligence (AI) has aroused interest in the growth and development of educational AI tools (EAITs). Teachers' adoption of EAITs in classrooms has helped in shaping instructional decisions taken by them in an attempt to promote intelligently and actively students' meaningful learning of contents areas. The present study showed that STM teachers' instructional beliefs were important predictors of their acceptance of EAITs, and that they are likely to adapt to EAITs when they are constructivist-oriented. Traditional instructional beliefs (TIB) had a negative influence on perceived trust (PT), perceived ease of use (PEOU), and perceived usefulness (PU). In addition, PT, PEOU and PU were strong factors predicting STM teachers' adoption of EAITs. However, PEOU was the strongest factor that predicted STM teachers' adoption of EAITs in pedagogical discourse. The results of the present study have functional and hypothetical implications. This study is first to be conducted in Nigeria as there is little empirical assessment of teachers' acceptance of EAITs. The study proposed an extended technology acceptance model (TAM) integrating STM teachers' perceived trust and instructional beliefs in EAITs. With the use of structural equation modeling (SEM), the proposed model was sufficiently necessary in predicting STM teachers' intentions to use EAITs. The results of this study are of practical benefits to EAIT developers, educational institutions, students and teachers. Adoption of EAITs not only helps to promote students' learning but also promotes teachers' understanding of their students and can reduce their cognitive load so that they spend more quality time with their students. More so, the present study results showed that when STM teachers are more constructivist inclined, they show the tendency to see EAITs as efficient, accessible and commodious, which may lend credence to their adoption in the instructional process. The implication of this is that schools should encourage STM teachers to be more constructivist inclined and provide opportunities for them through training programme to garner experience in using EAITs for the benefit of their students. Additionally, the results of this study could serve as a roadmap for developers of EAITs. Clearly, STM teachers will adopt EAITs when they realise that they are useful, user-friendly, easy to operate and beneficial to them and their students during instructional process. The implication of this is that EAIT developers should develop EAITs that are user-friendly, easy to use, easy to operate and configure, and reliable and trustworthy for the teachers and students.

The present study is not without limitations. First, this study was conducted within a very short period of time and thus did not consider the extent to which the STM teachers had been exposed to the EAITs. Spending longer time with EAITs might change the perceptions of the STM teachers regarding the EAITs. Future researchers should engage in longitudinal studies of STM teachers' perceptions of EAITs to establish whether their perceptions would change over time. Second, the biodata of the STM teachers were not given due consideration in this study. It is important to research into the effects of age, gender and teaching experience of the STM teachers on their behavioural intention to use EAITs during instructional process in the classroom. Third, the STM teachers were sampled from Lagos state out of the 36 states in Nigeria. It is possible that the STM teachers from the remaining 35 states of Nigeria with different cultural contexts may put up EAIT adoption structures that may be different from that of the study sample. Thus, future researchers in Nigeria may consider recruiting their samples from other parts of the country and also consider the demographics of the samples in their quest to determine their moderating effects on STM teachers' adoption of EAITs through the TAM framework. Lastly, this study did not collect qualitative data through focus group discussion or open-ended questions from the participants but relied only on the quantitative data collection process. A mixed-method research framework that combines both quantitative and qualitative data techniques may provide rich understanding of the fundamental mechanism beneath the STM teachers' adoption of EAITs in the classroom instructional process.

7 IMPLICATIONS

The AI-based educational technologies can have several implications for educators, system designers, and policymakers. For Educators: AI can tailor educational experiences to individual students' needs, learning styles, and paces. This will enhance student engagement and outcomes, but requires educators to adapt to new teaching methods and integrate AI tools into their curriculum. AI systems can provide real-time assessment and feedback, helping educators identify student strengths and areas for improvement. This will allow for more timely and effective interventions but may reduce the traditional role of educators in assessing student performance. AI can automate administrative tasks such as grading, scheduling, and resource management. This frees up time for educators to focus on teaching and student interaction, but requires them to learn and trust new systems. Continuous learning and adaptation to new AI tools will be essential. Educators need ongoing professional development to stay updated with the latest technologies and teaching strategies. For System Designers: Designing AI systems that are intuitive and user-friendly for both educators and students. This requires collaboration with educators to ensure that tools meet their needs and enhance the learning experience. Ensuring that AI systems comply with privacy laws and protect sensitive student data. This requires designing robust security measures and transparent data practices to build trust among users. Creating solutions that are scalable and accessible to diverse educational contexts and populations. This requires balancing advanced functionalities with affordability and simplicity to cater to a wide range of users. Addressing ethical concerns such as bias in AI algorithms and the digital divide. This requires implementing fair and unbiased AI systems and ensuring equitable access to technology for all students. For Policymakers: Developing policies and standards to regulate the use of AI in education. This will ensure that AI technologies are used ethically and effectively while protecting student rights and data privacy. Allocating resources and funding for the development and implementation of AI-based educational technologies. This will encourage innovation while ensuring that schools have the necessary infrastructure and support to integrate AI tools. Promoting policies that address the digital divide and ensure that all students have access to AI-enhanced education. This will ensure inclusivity by providing support and resources to underserved communities and schools. Providing training and support for educators to effectively use AI tools. This will help in implementing programs that help educators develop the skills needed to integrate AI into their teaching practices.

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REFERENCES

Akar, S. G. M. (2019). Does it matter being innovative: Teachers' technology acceptance. *Education and Information Technologies*, *24*(6), 3415–3432. https://doi.org/10.1007/s10639-019-09933-z.

Alexandrakis, D., Chorianopoulos, K., & Tselios, N. (2020). Older adults and web 2.0 storytelling technologies: Probing the technology acceptance model through an age-related perspective. *International Journal of Human–Computer Interaction*, *36*(17), 1623–1635. https://doi.org/10.1080/10447318.2020.1768673

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Arpaci, I. (2016). Understanding and predicting students' intention to use mobile cloud storage services. *Computers in Human Behavior*, *58*, 150–157. https://doi.org/10.1016/j.chb.2015.12.067.

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. *Journal of Medical Internet Research*, *22*(6), e15154. https://doi.org/10.2196/15154

Awofala, A. O. & Oladipo, A. J. (2023). A simulation study of preservice STM teachers' technostress as related to supposed utility, attitudes towards portable technology and continuance intents to use portable technology. *Digital Education Review, 44*, 23-29.

Awofala, A. O. A. & Ojaleye, O. (2018). An exploration of pre-service teachers' educational values of mathematics in relation to gender and attitudes toward mathematics in Nigeria. *Journal of Pedagogical Research, 2*(1), 1-15.

Awofala, A. O. A., Lawani, A. O. & Oraegbunam, C. O. (2019). An assessment of the psychometric properties of the conceptions of teaching and learning questionnaire by pre-service mathematics teachers in south-west, Nigeria. *International Journal of Pedagogy and Teacher Education, 3*(2), 89-102.

Awofala, A. O. A., Oladipo, A. J., Akinoso, S. O., Arigbabu, A. A., & Fatade, A. O. (2022). An assessment of google classroom reception and usage among pre-service science, technology and mathematics teachers in south-west Nigeria. *Jurnal Pendidikan Progresif, 12*(2), 796-805.

Awofala, A. O., & Sopekan, O. S. (2020). Early-years future teachers' mathematical beliefs as determinants of performance in primary mathematics. *JRAMathEdu (Journal of Research and Advances in Mathematics Education), 5*(1), 54-68.

Awofala, A. O., Lawani, A. O., & Oraegbunam, C. O. (2020). A factor analytic structure of the conceptions of mathematics scale among pre-service mathematics teachers in south-west Nigeria. *JRAMathEdu (Journal of Research and Advances in Mathematics Education), 5*(1), 94-104.

Bitkina, O. V., Jeong, H., Lee, B. C., Park, J., Park, J., & Kim, H. K. (2020). Perceived trust in artificial intelligence technologies: A preliminary study. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *30*(4), 282–290. https://doi.org/10.1002/hfm.20839

Chan, K.-W., & Elliott, R. G. (2004). Relational analysis of personal epistemology and conceptions about teaching and learning. *Teaching and Teacher Education*, *20*(8), 817–831. https://doi.org/10.1016/j.tate.2004.09.002

Chiu, T. K. F., & Churchill, D. (2016). Adoption of mobile devices in teaching: Changes in teacher beliefs, attitudes, and anxiety. *Interactive Learning Environments*, *24*(2), 317–327. https://doi.org/10.1080/10494820.2015.1113709

Choi, J. K., & Ji, Y. G. (2015). Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692–702. https://doi.org/10.1080/10447318.2015.1070549

Choi, S., Jang, Y., & Kim, H. (2023). Influence of Pedagogical Beliefs and Perceived Trust on Teachers' Acceptance of Educational Artificial Intelligence Tools. *International Journal of Human–Computer Interaction, 39*(4), 910-922. DOI: 10.1080/10447318.2022.2049145

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education*, *59*(2), 423–435. https://doi.org/10.1016/j.compedu.2012.02.001

Estriegana, R., Medina-Merodio, J. A., & Barchino, R. (2019). Student acceptance of virtual laboratory and practical work: An extension of the technology acceptance model. *Computers & Education*, *135*, 1–14. https://doi.org/10.1016/j.compedu.2019.02.010

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382–388. https://doi.org/10.1177/002224378101800313

Fraillon, J., Ainley, J., Schulz, W., Friedman, T., & Gebhardt, E. (2014). *Preparing for life in a digital age: The IEA International Computer and Information Literacy Study international report.* Springer Nature.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly: Management Information Systems*, *27*(1), 51–90. https://doi.org/10.2307/30036519

Gil-Flores, J., Rodríguez-Santero, J., & Torres-Gordillo, J. J. (2017). Factors that explain the use of ICT in secondary-education classrooms: The role of teacher characteristics and school infrastructure. *Computers in Human Behavior*, *68*, 441–449. https://doi.org/10.1016/j.chb.2016.11.057

Girish, V. G., Kim, M. Y., Sharma, I., & Lee, C. K. (2021). Examining the structural relationships among e-learning interactivity, uncertainty avoidance, and perceived risks of COVID-19: Applying extended technology acceptance model. *International Journal of Human–Computer Interaction*, 1–11. https://doi.org/10.1080/10447318.2021.1970430

Guilherme, A. (2019). AI and education: The importance of teacher and student relations. *AI & Society*, *34*(1), 47–54. https://doi.org/10.1007/s00146-017-0693-8

Gurer, M. D., & Akkaya, R. (2021). The influence of pedagogical beliefs on technology acceptance: A structural equation modeling study of pre-service mathematics teachers. *Journal of Mathematics Teacher Education*, 1–17. https://doi.org/10.1007/s10857-021-09504-5

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage publications.

Holstein, K., McLaren, B. M., & Aleven, V. (2018). Student Learning Benefits of a Mixed-Reality Teacher Awareness Tool in AI-Enhanced Classrooms. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 10947 LNAI, 154–168. https://doi.org/10.1007/978-3-319-93843-1_12

Hwang, Y., & Kim, D. J. (2007). Customer self-service systems: The effects of perceived web quality with service contents on enjoyment, anxiety, and e-trust. *Decision Support Systems*, *43*(3), 746–760. https://doi.org/10.1016/j.dss.2006.12.008

Jeon, J. (2022). Exploring AI chatbot affordances in the EFL classroom: Young learners' experiences and perspectives. *Computer Assisted Language Learning*, 1–26. https://doi.org/10.1080/09588221.2021.2021241

Johal, W., Castellano, G., Tanaka, F., & Okita, S. (2018). Robots for learning. *International Journal of Social Robotics*, *10*(3), 293–294. https://doi.org/10.1007/s12369-018-0481-8

Kim, C. M., Kim, M. K., Lee, C. J., Spector, J. M., & DeMeester, K. (2013). Teacher beliefs and technology integration. *Teaching and Teacher Education*, *29*(1), 76–85. https://doi.org/10.1016/j.tate.2012.08.005

Kim, J., Merrill, K., Xu, K., & Sellnow, D. D. (2020). My teacher is a machine: Understanding students' perceptions of AI teaching assistants in online education. *International Journal of Human–Computer Interaction*, *36*(20), 1902–1911. https://doi.org/10.1080/10447318.2020.1801227

Kline, R. B. (2015). TXTBK Principles and practices of structural equation modeling Ed. 4 ***. In Methodology in the social sciences.

Lano-Maduagu, A. T. Awofala, A. O. A., & Arigbabu, A. A. (2022). Assessment of psychometric properties of teachers' sense of efficacy beliefs by pre-service home economics teachers in southwest, Nigeria. *Nigerian Online Journal of Educational Sciences and Technology,* 4 (2), 89-99.

Liu, H., Lin, C. H., & Zhang, D. (2017). Pedagogical beliefs and attitudes toward information and communication technology: A survey of teachers of English as a foreign language in China. *Computer Assisted Language Learning*, *30*(8), 745–765. https://doi.org/10.1080/09588221.2017.1347572

Mercader, C., & Gairín, J. (2020). University teachers' perception of barriers to the use of digital technologies: The importance of the academic discipline. *International Journal of Educational Technology in Higher Education*, *17*(1), 1–14. https://doi.org/10.1186/s41239-020-0182-x

Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioral intention to use. *Computers & Education*, *109*, 56–73. https://doi.org/10.1016/j.compedu.2017.02.005

Nja, C. O., Idiege, K. J., Uwe, U. E. et al. (2023). Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers. *Smart Learning Environment, 10*, 42. https://doi.org/10.1186/s40561-023-00261-x.

Nye, B. D. (2014). Barriers to ITS Adoption: A systematic mapping study. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8474 LNCS, 583–590. https://doi.org/10.1007/978-3-319-07221-0_74

Pal, D., & Patra, S. (2021). University students' perception of video-based learning in times of COVID-19: A TAM/TTF perspective. *International Journal of Human–Computer Interaction*, *37*(10), 903–921. https://doi.org/10.1080/10447318.2020.1848164

Pawar, U., O'Shea, D., Rea, S., & O'Reilly, R. (2020). Explainable AI in Healthcare. 2020 International Conference on Cyber Situational Awareness, Data Analytics and Assessment, Cyber SA 2020. https://doi.org/10.1109/CyberSA49311.2020.9139655

Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L., & Sohl-Dickstein, J. (2015). Deep knowledge tracing. *Advances in Neural Information Processing Systems, 2015-Janua*, 505–513.

Qin, F., Li, K., & Yan, J. (2020). Understanding user trust in artificial intelligence-based educational systems: Evidence from China. *British Journal of Educational Technology*, *51*(5), 1693–1710. https://doi.org/10.1111/bjet.12994

Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile library applications with an extended Technology Acceptance Model (TAM). *Computers & Education*, *145*, 103732. https://doi.org/10.1016/j.compedu.2019.103732

Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science*, *48*(1), 137–141. https://doi.org/10.1007/s11747-019-00710-5

Riestra-González, M., Paule-Ruíz, M. d P., & Ortin, F. (2021). Massive LMS log data analysis for the early prediction of course-agnostic student performance. *Computers & Education*, *163*, 104108. https://doi.org/10.1016/j.compedu.2020.104108

Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. (2020). User acceptance of virtual reality: An extended technology acceptance model. *International Journal of Human–Computer Interaction*, *36*(11), 993–1007. https://doi.org/10.1080/10447318.2019.1708612

Sánchez-Prieto, J. C., Cruz-Benito, J., Therón, R., & García-Pẽalvo, F. J. (2019). How to measure teachers' acceptance of AI-driven assessment in e-learning: A TAM-based Proposal. *ACM International Conference Proceeding Series*, 181–186. https://doi.org/10.1145/3362789.3362918

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*(0317), 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Shin, D. (2021). The effects of explain ability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telematics and Informatics*, *47*, 101324. https://doi.org/10.1016/j.tele.2019.101324

Song, P., & Wang, X. (2020). A bibliometric analysis of worldwide educational artificial intelligence research development in recent twenty years. *Asia Pacific Education Review*, *21*(3), 473–486. https://doi.org/10.1007/s12564-020-09640-2

Sopekan, O. S. & Awofala, A. O. A. (2019). Mathematics anxiety and mathematics beliefs as correlates of early childhood pre-service teachers' numeracy skills. *Pedacta*, *9*(2), 13-24.

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development*, *65*(3), 555–575. https://doi.org/10.1007/s11423-016-9481-2

Troussas, C., Krouska, A., & Virvou, M. (2020). Using a multi-module model for learning analytics to predict learners' cognitive states and provide tailored learning pathways and assessment. In *Machine Learning Paradigms* (pp. 9–22). Springer.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Wallace, L. G., & Sheetz, S. D. (2014). The adoption of software measures: A Technology Acceptance Model (TAM) perspective. *Information & Management*, *51*(2), 249–259. https://doi.org/10.1016/j.im.2013.12.003

Wei, Y., Yang, Q., Chen, J., & Hu, J. (2018). The exploration of a machine learning approach for the assessment of learning styles changes. *Mechatronic Systems and Control*, *46*(3), 121–126. https://doi.org/10.2316/journal.201.2018.3.201-2979

Yin, M., Vaughan, J. W., & Wallach, H. (2019). Understanding the effect of accuracy on trust in machine learning models [Paper presentation]. Conference on Human Factors in Computing Systems – Proceedings. https://doi.org/10.1145/3290605.3300509

Zhang, Y., Vera Liao, Q., & Bellamy, R. K. E. (2020). Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making [Paper presentation]. FAT* 2020 – Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 295–305. https://doi.org/10.1145/3351095.3372852.

MODELATGE D'EQUACIONS ESTRUCTURALS DE L'ADOPCIÓ D'EINES EDUCATIVES D'INTEL·LIGÈNCIA ARTIFICIAL PER PART DE PROFESSORS DE CIÈNCIA, TECNOLOGIA I MATEMÀTIQUES DE NIGÈRIA

Els avenços recents en intel·ligència artificial (IA) han despertat interès en el creixement i el desenvolupament d'eines educatives d'IA (EAIT). L'adopció d'EAIT per part dels docents a les aules ha ajudat a donar forma a les decisions d'instrucció que prenen en un intent de promoure de manera intel·ligent i activa l'aprenentatge significatiu de les àrees de contingut dels estudiants. No obstant això, els professors de ciència, tecnologia i matemàtiques (CTM) a Nigèria poques vegades adopten i incorporen EAIT en el discurs pedagògic de les seves aules, i les seves percepcions sobre els EAIT poques vegades s'avaluen. A aquest efecte, aquest estudi va identificar factors humans en l'acceptació d'EAIT per part de professors de STM a Nigèria. L'estudi va proposar un model estès d'acceptació de tecnologia (TAM) que integra la confiança percebuda dels professors de STM i les creences educatives als EAIT mitjançant un model quantitatiu d'un disseny d'enquesta descriptiu. La mostra per a l'estudi va estar composta per 345 professors de STM als sis districtes educatius de l'estat de Lagos, Nigèria. L'estudi va proposar un model estès d'acceptació de tecnologia (TAM) que integra la confiança percebuda dels professors de STM i les creences educatives als EAIT mitjançant un model quantitatiu d'un disseny d'enquesta descriptiu. La mostra per a l'estudi va estar composta per 345 professors de STM als sis districtes educatius de l'estat de Lagos, Nigèria. Es va fer servir un instrument vàlid i fiable etiquetatge com a qüestionari d'adopció d'eines educatives d'intel·ligència artificial (AEAITQ, α = 0,87) per recopilar dades de l'enquesta que es van analitzar mitjançant models d'equacions estructurals. Els resultats de l‟estudi van mostrar que els professors de STM amb creences constructivistes tenien la tendència a adoptar i incorporar EAIT en les seves decisions d‟instrucció que els seus homòlegs amb creences tradicionals. Les creences educatives tradicionals (TIB) van tenir una influència negativa en la confiança percebuda (PT), la facilitat d'ús percebuda (PEOU) i la utilitat percebuda (PU). A més, PT, PEOU i PU van ser factors importants que van predir l'adopció d'EAIT per part dels professors de STM. Tot i això, PEOU va ser el factor més fort que va predir l'adopció d'EAIT per part dels professors de STM en el discurs pedagògic. Es van debatre conclusions importants sobre el creixement i l'adopció de les EAIT per part dels principals interessats en l'ensenyament de les ciències, la tecnologia i les matemàtiques.

PARAULES CLAU: Modelatge d'equacions estructurals, professors nigerians, de ciència, tecnologia i matemàtiques, adopció, eines educatives d'intel·ligència artificial.

MODELADO DE ECUACIONES ESTRUCTURALES DE LA ADOPCIÓN DE HERRAMIENTAS EDUCATIVAS DE INTELIGENCIA ARTIFICIAL POR PARTE DE PROFESORES DE CIENCIA, TECNOLOGÍA Y MATEMÁTICAS DE NIGERIA

Los avances recientes en inteligencia artificial (IA) han despertado interés en el crecimiento y desarrollo de herramientas educativas de IA (EAIT). La adopción de EAIT por parte de los docentes en las aulas ha ayudado a dar forma a las decisiones de instrucción que toman en un intento de promover de manera inteligente y activa el aprendizaje significativo de las áreas de contenido de los estudiantes. Sin embargo, los profesores de ciencia, tecnología y matemáticas (CTM) en Nigeria rara vez adoptan e incorporan EAIT en el discurso pedagógico de sus aulas, y sus percepciones sobre los EAIT rara vez se evalúan. Con este fin, este estudio identificó factores humanos en la aceptación de EAIT por parte de profesores de STM en Nigeria. El estudio propuso un modelo extendido de aceptación de tecnología (TAM) que integra la confianza percibida de los profesores de STM y las creencias educativas en los EAIT a través de un modelo cuantitativo de un diseño de encuesta descriptivo. La muestra para el estudio estuvo compuesta por 345 profesores de STM en los seis distritos educativos del estado de Lagos, Nigeria. Se utilizó un instrumento válido y confiable etiquetado como cuestionario de adopción de herramientas educativas de inteligencia artificial (AEAITQ, α = 0,87) para recopilar datos de la encuesta que se analizaron mediante modelos de ecuaciones estructurales. Los resultados del estudio mostraron que los profesores de STM con creencias constructivistas tenían la tendencia a adoptar e incorporar EAIT en sus decisiones de instrucción que sus homólogos con creencias tradicionales. Las creencias educativas tradicionales (TIB) tuvieron una influencia negativa en la confianza percibida (PT), la facilidad de uso percibida (PEOU) y la utilidad percibida (PU). Además, PT, PEOU y PU fueron factores importantes que predijeron la adopción de EAIT por parte de los profesores de STM. Sin embargo, PEOU fue el factor más fuerte que predijo la adopción de EAIT por parte de los profesores de STM en el discurso pedagógico. Se debatieron importantes conclusiones sobre el crecimiento y la adopción de las EAIT por parte de los principales interesados en la enseñanza de las ciencias, la tecnología y las matemáticas.

PALABRAS CLAVE: Modelado de ecuaciones estructurales, profesores nigerianos, de ciencia, tecnología y matemáticas, adopción, herramientas educativas de inteligencia artificial.

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