

AN EMOTIONAL EXPECTANCY CONSTRUCTION IN A UNIFIED THEORY OF ACCEPTANCE AND USE OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN NIGERIA

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Abstract

*The Unified Theory of Acceptance and Use of Technology (UTAUT) model theorizes that four constructs play a significant role as direct determinants of user acceptance and usage behavior: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Even though several researchers discuss the relevance of EE in user acceptance of new technologies, the UTAUT model does not use EE as a direct determinant. This study argues that EE is a direct determinant of behavioral intention. **Aim:** The aim of this research is to construct an emotional expectancy model in a unified theory of acceptance for the use of AI technology, provided by the Nigerian context. The study conducted a quantitative study by using a questionnaire distributed via emails and WhatsApp to examine the impact of EE on the behavior intention to adopt AI technology among Nigerians. Seven hypotheses were tested, and results indicated that PE significantly influenced BI ($\beta = .357, p < .05$), suggesting that respondents had positive attitudes toward AI services. SI also had a positive influence on BI ($\beta = .161, p > .05$), highlighting the role of social acceptance in AI adoption. FC was found to significantly influence BI ($\beta = .116, p < .05$), indicating that users are more likely to adopt AI if they have the necessary resources and support. EE, however, did not significantly impact BI ($\beta = .010, p > .05$), contradicting previous studies that emphasized its importance. Internet trust and PE were the strongest predictors of AI adoption. Given EE's limited influence, the study proposes extending the UTAUT model by incorporating Emotional Expectancy as a new construct to better understand AI adoption in Nigeria. The research provides valuable insights for policymakers and technology planners to enhance AI acceptance by addressing key determinants.*

Keywords: Artificial Intelligence, Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, Performance Expectancy, Effort Expectancy.

1. Introduction

Artificial Intelligence (AI) is transforming various sectors globally, enhancing efficiency, decision-making, and user experiences. In Nigeria, AI adoption is steadily increasing, influencing industries such as healthcare, finance, education, and public administration (Folorunso et al., 2024). However, the acceptance and use of AI technologies remain complex, influenced by multiple factors beyond traditional usability and functionality considerations (Ling et al., 2021). Existing models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), provide a structured framework for understanding technology adoption by incorporating key constructs like performance expectancy and effort expectancy. These constructs primarily focus on an individual's perception of a technology's usefulness and ease of use. Several researchers developed theories and models to describe and analyze user acceptance and each of these models determines different factors to explain user acceptance (Motamedi et al., 2021). The question about user acceptance is related to all researchers who want to presage which technologies will prove appropriate for an organization. On the other hand, user acceptance is very important to the successful implementation of any new technology. Additionally, it is significant to note that technology's features play a vital role in determining whether individuals involved in activity will use it or not. Thus, understanding the users' perception towards the adoption of new technology could help facilitate further growth of the implementation of that particular technology. Technology acceptance models and theories have been applied in a wide variety of domains to understand and to predict users' behaviour such as voting, dieting, family planning, donating blood, women's occupational orientations, breast cancer examination, choice of transport mode, turnover, using birth control pills, education, consumer's purchase behaviours, and computer usage (Hwang et al., 2021; Lee & Wong, 2021; Malhotra et al., 2020; Motamedi et al., 2021). Many researchers in the field of technology acceptance, developed frameworks and models to assess the usage of new technologies and these models introduce factors that can affect user acceptance such as Theory of Reasoned Action (TRA) (Rossmann, 2021), Theory of Interpersonal Behaviour (TIB) (Derakhshan, 2022), Social Cognitive Theory (SCT) (Almogren & Aljammaz, 2022), Theory of Planned Behaviour (TPB) (Astari et al., 2022), Diffusion of Innovation Theory (DIT) (Al-Rahmi et al., 2019; Yuen et al., 2022), Technology Acceptance Model (TAM) (Davis & Granic, 2024), Extension of TAM (Singh & Ghatak, 2021; Jimenez et al., 2021), Motivational Model (MM) (Granic, 2022), Uses and Gratification Theory (UGT), Model of PC Utilization (MPCU) (Mohamed et al., 2021), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, 2021), and E-Service Technology Acceptance Model (ESAM) (Taherdoost, 2019) and many studies have used these traditional

frameworks to conduct their researches and the rest combined previous models or add new constructs to develop models to carry out their study. TAM and UTAUT suggest that the actual use of technology is affected by one's behavioural intention to use it. In TAM, the intended use is determined by attitude toward using the technology, which in turn is determined by two perceptions of the system: perceived usefulness and perceived ease of use. Various external factors affect both perceptions. UTAUT builds on TAM, as well as seven other theoretical frameworks. It proposes four constructs that affect usage intention performance expectancy, effort expectancy, social influence and facilitating conditions. Age, gender, experience, and voluntariness of use mediate the impact of these expectancies and facilitating conditions on intention. Both TAM and UTAUT have been used extensively in Management Information Systems (MIS) and biomedical informatics (Bagheri et al., 2021; Cornacchia et al., 2020) and many modifications and adaptations of these theories have been proposed over the years. This includes, for example, adding constructs from other theories and modifications to account for specific applications such as telemedicine or patients' adoption of eHealth and m-Health application (Rouidi et al., 2022). However, these theories (especially TAM) have also been widely criticized. There are further factors that should be added in the TAM and UTUAT according to the individual and environment characteristics. The current study will focus only on the UTUAT model to further extend it by adding human and environmental characteristics.

2. Related Works

Rahi et al. (2019), revealed that the integrated UTAUT model had a significant influence on user intention to adopt internet banking. Also, the SEM indicated that approximately 80 per cent of the variance in user intention to adopt internet banking was accounted for by predictors. The study schematized that assurance is the most influential factor among all other technology and service quality factors. Additionally, performance expectancy was found to be positive and significant mediator variables among website design, customer service and customers' intention to adopt internet banking. In the same regard Aijaz et al. (2021) suggested that research on the effect of risk in the adoption process remains inconclusive. Contrarily, consumers have overcome many fears due to the usefulness, indispensability, high-security features, and effort expended in the use of financial services delivered through m-banking. Perceived risk's (PR) direct influence was found to be generally weak. However, PR plays a major role in the pre-adoption process because it is weak and direct inhibiting influence becomes an "enhancer" in the association between effort expectancy (EE) and the three key TAM/UTAUT constructs including performance expectancy (PE), attitude (ATT), and adoption intention (INT). Most importantly, the role of PE, ATT, INT, and its significant interaction with PR

highlights the unique role that both risk and EE play in the adoption process. Kim et al. (2021), revealed that Performance Expectancy of Officiating Technology (PEOT) had a positive and direct impact on attitude toward and intention to watch sports events. In addition, attitude partially mediated the relationship between performance expectancy and intention to watch sports events. Also, Isaac et al. (2020) showed that while performance expectancy was significant in determining the intention to adopt an e-voting system, effort expectancy does not. However, effort expectancy was found to be a positive determinant of the performance expectancy of an electronic voting system. Also, citizen trust in institutions positively predicts both the performance and effort expectancy of an electronic voting system and the intention to use an electronic voting system. Paderanga et al. (2023) asserted that despite the growing interest in AI, there is limited research on accountants' perceptions and their willingness to embrace AI, especially in the the United Arab Emirates UAE. The study addressed this gap by examining accountants' perceptions of AI adoption in the UAE and developing a framework to understand the factors influencing their attitudes and behavioral intentions toward AI use in accounting. A survey was conducted among 96 accountants in (UAE) to validate the proposed model. The study employed empirical analysis to assess the relationship between perceived benefits, risks, attitudes, and behavioral intentions regarding AI adoption. The findings provide insights into accountants' perceptions of AI and confirm the effectiveness of the Integrated AI Acceptance-Avoidance Model (IAAAM) in explaining their attitudes and behavioral intentions. However, a significant gap exists between accountants' intention to use AI and its actual implementation. The study emphasizes the need for organizational support, enabling technologies, and skill development initiatives to enhance AI adoption. While Amadi (2021), investigated the role of policy in the acceptance and use of IT in the Nigerian healthcare system, focusing on medical practitioners' perceptions of its usefulness and ease of use. A quantitative approach was used, employing an extended TAM. Data were collected through a survey questionnaire from 272 medical practitioners at the National Hospital in Abuja, Nigeria. Findings revealed that policy, perceived usefulness, and perceived ease of use positively influence medical practitioners' intention to adopt IT. Additionally, policy affects how practitioners perceive the usefulness and ease of IT adoption in healthcare. AL-Nuaimi et al. (2022) extended the UTAUT and Diffusion of Innovation Theory (DIT) to examine factors influencing the acceptance and adoption of learning Management system (LMS) among students and faculty in a higher education institution in Oman, employing a cross-sectional survey study among undergraduate students and faculty in a higher education institution in Oman. Findings revealed that Perceived corona fear significantly influenced effort expectancy and performance expectancy in LMS adoption. Facilitating conditions and technological innovativeness, contrary to expectations, did not significantly affect the intention to adopt LMS suggesting a practical strategy for enhancing online learning elements within blended learning

models in higher education institutions post-pandemic. While Al-Adwan et al. (2021) extended The UTAUT model with three additional constructs: Learning tradition, Self-directed learning, E-learning self-efficacy. An online survey of 590 students from three private universities in Jordan was done, using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypotheses. Results indicates Positive influences on continued LMS usage: Performance expectancy, E-learning self-efficacy, Effort expectancy, facilitating conditions, social influence, Effort expectancy positively affects performance expectancy. Performance expectancy partially mediates the relationship between effort expectancy and continued usage intentions. Negative influences on continued LMS usage: Self-directed learning, Learning tradition. Obong (2024), explored the future need for AI-driven automated educational broadcasting in Nigeria. It argues that adopting automated processes, protocols, and resources in educational broadcasting will have both functional and dysfunctional impacts on learning outcomes study examined how AI-driven automation can transform educational broadcasting in Nigeria and proposes a framework for its successful implementation. The study adopted a futuristic technesis approach, drawing on two techno-deterministic theories: UTAUT and Media Ecology Theory. The study presupposes that AI-driven automation will create multi-layered effects in educational broadcasting, influencing learning contexts positively and negatively. Chen et al. (2020) identified the key factors that impact the adoption of IoT among construction industry practitioners in Taiwan using the Unified Theory of Acceptance and Use of Technology framework. A comprehensive literature review informed the development of the UTAUT-based hypotheses and a pilot study was conducted among experienced practitioners to refine the questionnaire. The final questionnaire (with 31 stems across 7 aspects) was distributed, 282 valid responses were collected. Six types of analysis were applied: Descriptive statistics, Reliability analysis, Validity analysis, t-test, One-way ANOVA, and Structural Equation Modeling (SEM). The study found that the following factors significantly influence practitioners' willingness to adopt IoT: Anticipated benefits, Anticipated efforts, and Societal expectations. The study focused on construction industry in Taiwan and recommends further research could explore different countries or industries for comparative insights. Camilleri (2024), identified key factors that drive users' acceptance and habitual engagement with AI chatbots, using established IT adoption models. A survey questionnaire was used to collect quantitative data from 654 respondents. Constructs were evaluated using the PLS approach via SmartPLS4. The study assessed: Reliability and validity of the constructs. Causal relationships in the proposed research model, findings revealed Source trustworthiness significantly affects performance expectancy of AI chatbots. Perceived interactivity strongly influences users' intentions to use AI chatbots. Other significant relationships were found between various IT adoption constructs.

2.1 Theoretical Review

The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most popular frameworks in the field of general technology acceptance models. Like earlier acceptance models, it aims to explain user intentions to use an IS and further the usage behaviour (Chen et al., 2020). Venkatesh, created this synthesized model to present a more complete picture of the acceptance process than was possible with any previous individual models. Eight models previously used in the IS field were merged in an integrated model, all of which had their origins in psychology, sociology, and communications. These models are the TRA, TPB, TAM, TAM2, the Motivational Model (MM), the Model of PC Utilization (MPCU), DOI, and Social Cognitive Theory (SCT). Each model attempts to predict and explain user behaviour using a variety of independent variables. A unified model was created based on the conceptual and empirical similarities across these eight models. The theory holds that four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) are direct determinants of usage intention and behaviour. Gender, age, experience, and voluntariness of use are posited to mediate the impact of the four key constructs on usage intention and behaviour as indicated in Figure 2. Moreover, the UTAUT model attempts to explain how individual differences influence technology use. More specifically, the relationship between perceived usefulness, ease of use, and intention to use can be moderated by age, gender, and experience. For example, the strength between perceived usefulness and intention to use varies with age and gender such that it is more significant for male and younger workers. The effect of perceived ease of use on intention is also moderated by gender and age, such that it is more significant for female and older workers, and those effects decrease with experience. The UTAUT has four predictors of behavioural intention or usage: performance expectancy, effort expectancy, social influence and facilitating conditions. In the UTAUT model, Effort Expectancy (EE) captures the notions of perceived ease of use and complexity. Ease of use is the second component in the classic study by Davis in 1989 and is generally believed to have a significant influence on technology acceptance as well as perceptions of usefulness. In validation of the UTAUT, EE was significant in both voluntary and mandatory usage contexts, although only for the first period of usage. Since practice increases one's comfort with software, effort-oriented constructs would become, logically, less salient after learning hurdles are overcome. Social influence includes consideration of the person's perception of the opinion of others, his or her reference group's subjective culture, and specific interpersonal agreements with others, as well as the degree to which use of an innovation is perceived to enhance one's image or status in one's social system (Shah & Asghar, 2023). This encompasses constructs from previous models such as subjective norms, social factors, and image. This construct suggests that an auditor would be sensitive to the opinions of others, resulting in

decisions consistent with the social norms around them. In their validation tests, Venkatesh found that social influence was not significant in voluntary contexts but becomes important when its use is mandated. Facilitating conditions (FC) represents organizational support and includes the constructs of perceived behavioural control, facilitating conditions, and compatibility from prior models. Results from the UTAUT validation suggest that FC was significant in both voluntary and mandatory settings in the initial usage period, but its influence on usage intentions disappeared after this. Additionally, FC appears to be fully moderated by effort expectancy, such that, when both PE and EE are present, FC becomes non-significant in predicting intention. UTAUT is a comprehensive model that described roughly 70% of the variance in behavioural intention in technology acceptance and usage, many studies confirmed the acceptability of the UTAUT model in new technology context (Chen et al., 2020; Nerves et al., 2024). But the majority of the studies that used the UTAUT model have been conducted in developed countries and have not been widely tested in developing countries such as Nigeria. The UTAUT model has been applied and tested extensively for predicting system usage and making technology-adoption- and technology-usage-related decisions in various fields such as Education (Al-Adwan et al., 2021), Energy Conservation (Ansu-Measa & Bein, 2019), Health (Akinuwesi et al., 2021), Business (Usman & Ibrahim, 2020) Applied research regarding the UTAUT model has been extensive. This model provides a framework that not only explains the acceptance of IT and ISs but also elucidates the actual use of such technologies and systems. Because of its capability to integrate different TAMs, the UTAUT model contributes substantially to the exploration of technology acceptance and usage (Nerves et al., 2024). Therefore, this study used the UTAUT model as the theoretical basis to evaluate the influences of technology-related factors. Although the UTAUT model has been widely adopted, doubts exist over its capability to explain individuals' technology acceptance. Thus, the original UTAUT model has been extended by researchers (De BlanesSebastian et al., 2022; Gansser & Reich, 2021; AL-Adwan et al., 2022). As mentioned, the present study proposed an extension of the UTAUT model by adding variables of emotional expectancy to predict adoption .The UTAUT model was adopted and extended by incorporating the constructs of emotional expectancy to investigate its influence on the behavioural intentions toward using the newly adopted UTAUT model. The combined and streamlined model features four core variables that predict behavioural intention and actual use: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating conditions (FC). PE relates to the belief that using the technology will help the user to perform their job better, EE captures the degree of ease that the user associates with the technology, SI indicates how the users perceive that others who are important to them (peers, supervisors) believe that they should use the technology and, lastly, FC is a scale that encompasses the degree to which participants believe training, support, infrastructure, as well as the background knowledge are available

to use the system optimally and was originally defined as the belief that organizational and technical infrastructure exists to support the use of the new technology (Ambarwati et al., 2020). Acceptance is a key concept within the UTAUT model, defined as users who willingly use a “technology for the tasks it is designed to support” (Garone et al., 2019). The most common ways to operationalize acceptance is through measuring or observing actual use behaviour and behavioural intention. However, it is not always possible to measure actual use. Other predictors that are sometimes used in connection with UTAUT scales, the original UTAUT is not enough to cause the intention (Krismadinata, 2019). The UTAUT model has been amended and modified in many ways to suit the study of different contexts (Tang et al., 2021). The original UTAUT along with the four key scales (PE, EE, SI and FC), continues to be the foundation for many technologies acceptance studies. While the UTAUT has been extensively validated across diverse technologies and contexts, most studies have primarily focused on cognitive and utilitarian factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. However, the emotional dimension of technology acceptance has been largely overlooked. Previous research has identified performance and effort expectancy as significant predictors of behavioral intention, but the internal emotional forces influencing users’ intentions remain underexplored. This omission represents a critical gap, as emotions are known to shape decision-making and behavioral intentions in technology adoption. As Al-Adwan et al. (2021) recommended, there is a need for further extension of the UTAUT model to incorporate emotional aspects. Therefore, the present study addresses this limitation by extending the UTAUT model to include emotional expectancy a construct that captures users anticipated emotional responses towards technology use. By integrating emotional expectancy into the UTAUT framework, this study aims to provide a more holistic understanding of technology adoption behaviors, especially in contexts where emotions may significantly impact users’ intention to adopt new technologies.

3. Methodology

This study adopts a quantitative survey research design. The target population comprises professionals and technology users in Nigeria familiar with Artificial Intelligence applications. Non probability sampling technique, in particular, purposive sampling technique was employed to ensure the inclusion of respondents with relevant experience. A structured questionnaire based on the UTAUT model extended with Emotional Expectancy (EE) was administered. The constructs measured include: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Emotional Expectancy (EME), with Behavioral Intention (BI) as the dependent variable.

The conceptual model is shown in Figure 3.1. Emotional Expectancy is introduced as a new variable hypothesized to have a significant impact on Behavioral Intention.

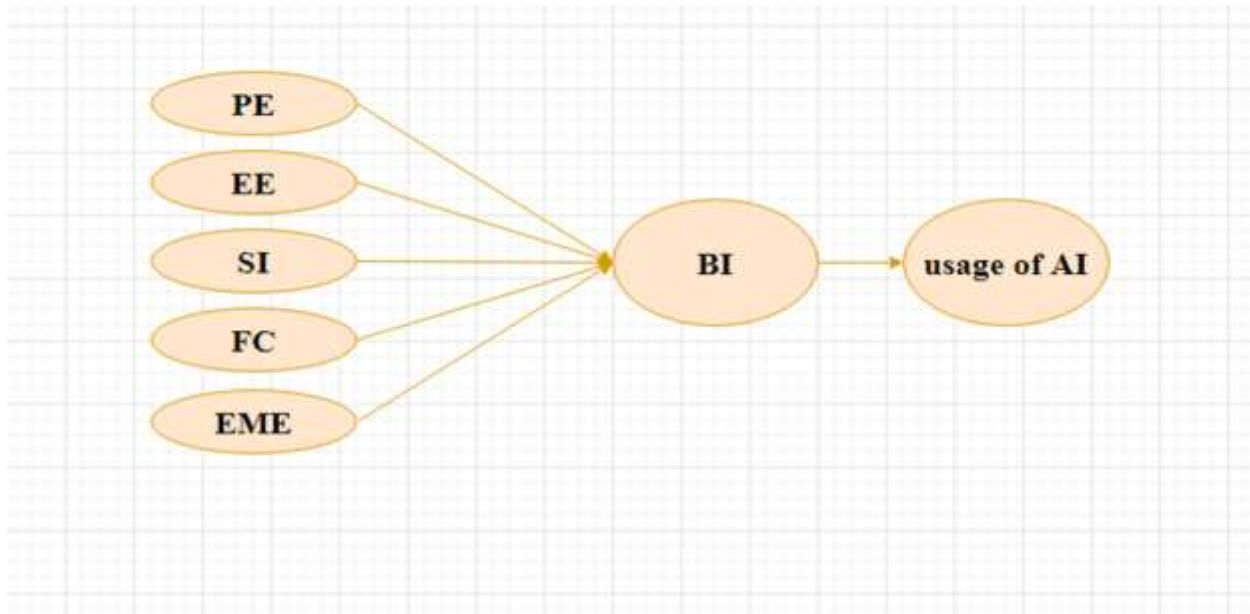


Figure 1: The Extended UTAUT

3.1 Population

Population is “the entire group of people, events, or things of interest that the researcher wishes to investigate” and ‘sample’, as the selected subset of a population, otherwise known as the study population (Hu, 2023). Researchers choose a certain number of samples out of the entire population for analysis and draw conclusions that can be applied to the population at large. In this research, the target population will be AI users in Nigeria, those who have once used services containing AI technology, both current users and former users, while the sample is narrowed down to those who have once used an AI technology and have given voluntary responses to the survey questionnaires.

3.2 Unit of Analysis

Unit of analysis is the level to which data are aggregated, which include individuals, dyads (two-person groups), groups, organizations, and cultures (Gonzalez & Poast, 2022). The selection of the type of units depends on the research interest and research problem. In this research, the individual unit of analysis will be adopted, because the aim of this research is to investigate factors influencing the usage

of AI technology in Nigeria at the individual level. The questions in the questionnaire survey will be design for individuals who are AI users in Nigeria, with the purpose of collecting detailed information from each respondent. Since individuals, in spite of their ages, genders, educational levels, occupations and income have their different perspectives on continued use of AI or trying new functions, this research aims to explore further into the influencing factors by taking each participant's response into account. The first phase was concerned with the preliminary analysis of data through pilot testing. This phase is important in order to ensure that the data met the basic requirements before proceeding with mass data collection. In the second stage, the data were analyzed using the PLS-SEM approach. The research model used in this study was managed to meet the requirements of the validity and reliability tests. After that, the structural model test was performed in order to examine the hypotheses developed.

3.3 Sampling Technique

Sampling techniques in which the probability of each case selected from the larger population can be known and would never be zero (Lakens, 2022). In comparison, non-probability sampling is the selection of sampling techniques in which the chance of each case being selected is unknown (Pace, 2021). Probability sampling is much more expensive and complicated than nonprobability sampling because the latter can be done with any people who are available (Kalton, 2023). Yet, probability sampling normally can claim the representative nature of a sample, but this is usually not boasted by nonprobability sampling. This study will use non-probability sampling as the sampling strategy. In order to minimize the sample errors, this research will limit the target sample to current and former users of AI technology in Nigeria in order to pursue the representativeness of the sample for the target population, which comprises all individuals in Nigeria with AI technology usage experience.

3.4 Sample Size

Sample size determination is the act of choosing the number of observations or replicates to include in a statistical sample (Lakens, 2022). The sample size is an important feature of any empirical study in which the goal is to make inferences about a population from a sample. A collection of the data from each follower of these pages is impossible, thus, potential representative samples will be drawn through purposive sampling.

3.5 Measurement

The scales for the UTAUT constructs (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention) was adapted from (Chen, 2020). The emotional expectancy scale will be drawn from (Abikari, 2021), All items will be measured using a five-point Likert scale, with the anchors being “strongly disagree” and “strongly agree.”

4 Results and Discussion

A total of 213 valid responses were analyzed using PLS-SEM. Descriptive statistics showed that Social Influence (M = 4.45, SD = 0.85), Facilitating Conditions (M = 3.80, SD = 1.02), and Effort Expectancy (M = 3.79, SD = 0.90) were rated highly among participants. Cronbach’s Alpha values for all constructs exceeded 0.7, indicating good internal consistency.

The structural model explained 55.2% of the variance in Behavioral Intention ($R^2 = 0.552$) and 25.2% in Actual AI Use ($R^2 = 0.252$). Performance Expectancy ($\beta = 0.357$, $p < .001$), Emotional Expectancy ($\beta = 0.290$, $p < .001$), Social Influence ($\beta = 0.161$, $p = .001$), and Facilitating Conditions ($\beta = 0.116$, $p = .006$) had significant positive effects on Behavioral Intention. Effort Expectancy ($\beta = -0.010$, $p = .801$) was not a significant predictor. Behavioral Intention significantly influenced Actual AI Use ($\beta = 0.502$, $p < .001$). These findings suggest that users’ performance-related beliefs, emotional engagement, and social environment play a critical role in shaping their intention to adopt AI technologies in Nigeria

4.1 Mean and Standard Deviation of the Study Variables

All six variables of the research study were measured on a five-point Likert scale, i.e., (1) strongly disagree to (5) strongly agree. In the five-point Likert scale, the mean value of latent variable less than or equal to 1.99 is considered as low, between 2.00 to 3.99 is moderate, and 4.00 and higher is high (Ahmed et al., 2024). However, only Actual behaviour was measured on a 7-point Likert scale with an average mean of 3.5. Table 1 shows the mean values and standard deviation of all the study constructs.

Table 1: Mean and Standard Deviation

Variable	Mean	Standard Deviation
PE	3.653	0.938
EE	3.789	0.897
SI	4.447	0.848
FC	3.804	1.018
AIU	5.573	1.438

BI	3.772	1.002
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4.2 Common Method Variance (CMV)

The common method variance (CMV) test for this study was based on Harmon’s single-factor analysis. CMV was required to be examined for the study, as the questionnaire data collected for predictor and criterion variables were obtained from the same respondent. The data collected using a cross-sectional survey method, CMV can be a potential problem, common method bias is problematic if a single latent factor would account for the majority of the variance explained (Maier et al., 2023). In this study, an un-rotated principal component factor analysis on all measurement items was performed, which extracted four factors with eigenvalues greater than 1.0, which made up 68.83% of the total variance. As shown in Table 2, factor one accounted for only 22.74% of the variance, thus the common method variance does not appear to be a significant issue in this study.

Table 2: Common Method Variance

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% Of Variance	Cumulative %	Total	% Of Variance	Cumulative %
1	9.327	22.748	22.748	9.327	22.748	22.748
2	4.185	10.208	32.956	4.185	10.208	32.956
3	3.747	9.140	42.096	3.747	9.140	42.096
4	2.685	6.548	48.644	2.685	6.548	48.644
5	2.223	5.421	54.065	2.223	5.421	54.065
6	2.111	5.150	59.215	2.111	5.150	59.215
7	1.967	4.798	64.013	1.967	4.798	64.013
8	1.170	2.854	66.867	1.170	2.854	66.867
9	1.083	2.642	69.509	1.083	2.642	69.509
10	.997	2.431	71.940			
11	.910	2.219	74.159			
12	.840	2.049	76.208			
13	.786	1.918	78.126			
14	.686	1.673	79.799			
15	.680	1.658	81.457			
16	.616	1.503	82.960			
17	.604	1.472	84.432			
18	.566	1.381	85.813			
19	.499	1.216	87.030			
20	.449	1.095	88.125			

21	.432	1.055	89.179			
22	.415	1.012	90.191			
23	.380	.928	91.119			
24	.362	.882	92.001			
25	.349	.850	92.851			
26	.321	.783	93.635			
27	.300	.733	94.368			
28	.267	.651	95.019			
29	.249	.607	95.626			
30	.241	.588	96.214			
31	.223	.544	96.758			
32	.197	.481	97.239			
33	.181	.441	97.680			
34	.174	.425	98.105			
35	.166	.406	98.511			
36	.161	.394	98.905			
37	.151	.368	99.273			
38	.132	.322	99.595			
39	.085	.207	99.802			
40	.052	.126	99.928			
41	.030	.072	100.000			

Extraction Method: Principal Component Analysis.

4.3 Assessment of Measurement Model

The first step in PLS analysis is, to assess the measurement model, this is required to determine how good the measurement items were when loaded on theoretical defined constructs. Two main indicators used for evaluating the measurement model were validity and reliability. The study follows the recommendation of Yousif et al. (2019), used to explain how the reflective model for PLS-SEM should be analysed for internal consistency, indicator reliability, convergent validity, and discriminant validity before evaluating the structural model.

4.3.1 Construct Validity

This study performed measurement validity (or construct validity) in order to examine the degree of measurement that applies to conceptual model or theory. There are two components of measurement validity that were tested in this study: (1) convergent validity and (2) discriminant validity. The measurement validity is important, and it was used to determine whether the assessment of construct represented by the measurement is reliable or not.

4.3.1.1 Convergent Validity

Convergent validity or the extent to which measure correlates with alternate measures of the same construct was examined using the outer loading of indicators and the average variance extracted (AVE). The outer loadings and AVE for exogenous and endogenous variables are tabulated in Table 3. The AVE for all the latent variables exceeded the recommended value of 0.50 (Cheung et al., 2023). This indicated that the variance extracted from items loading were more than one-half of the variance observed. The study used a Structural Equation Model (SEM) with the PLS approach and applied smart PLS 3.2.8 data analysis tool to achieve the objectives of the study and analyze the measurement and structural models. At first, the convergent validity of the model was analyzed which included indicator loading, average variance extracted (AVE), and composite reliability (CR). Table 3 shows the indicator loadings for all the items that exceeded the recommended value of 0.508. However, two items SI4 and EE4 were deleted with factor loading less than 0.50 (-0.234) as the AVE of the latent variable of this item was also not more than the recommended value of 0.50. The AVE of all variables was in the range of 0.619 to 0.841, which exceed the recommended value of 0.50, and CR ranges from 0.830 to 0.922, which exceed the recommended value of 0.70 given by Ansu-Mensah and Bein (2019). Thus, this study ensured the existence of convergent validity.

Table 3: The Results of Measurement Model

Variables	Items	Loadings	Cronbach's Alpha	CR	AVE
AIU	AIU1	0.812	0.785	0.874	0.698
	AIU2	0.853			
	AIU3	0.84			
BI	BI1	0.863	0.779	0.871	0.693
	BI2	0.857			
	BI3	0.775			

EE	EE1	0.854	0.91	0.936	0.787
	EE2	0.903			
	EE3	0.913			
	EE4	0.876			
EME	EME1	0.861	0.897	0.928	0.764
	EME2	0.861			
	EME3	0.891			
	EME4	0.882			
FC	FC1	0.822	0.769	0.866	0.683
	FC2	0.86			
	FC3	0.796			
PE	PE1	0.834	0.807	0.873	0.633
	PE2	0.723			
	PE3	0.828			
	PE4	0.792			
SI	SI1	0.849	0.828	0.897	0.744
	SI2	0.895			
	SI3	0.842			

4.3.1.2 Discriminant Validity

The discriminant validity of the model was also tested by Heterotrait-Monotrait (HTMT) ratio. Guenther et al. (2023), explained that the HTMT ratio is a superior criterion as compared to other methods such as the Fornell-Larcker criterion. They suggested two different cut-off values of 0.85 and 0.90 for the HTMT criterion to establish discriminant validity. The study used the 0.90 criterion (i.e., HTMT_{.90}) to establish the discriminant validity of the model. Table 4 shows that the discriminant validity of the model was established since all the results of the HTMT_{.90} criterion were below the critical value of 0.90. Overall, the measurement model has shown adequate convergent and discriminant validity.

Table 4: Discriminant Validity (HTMT₉₀)

Variables	AIU	BI	EE	EME	FC	PE	SI
AIU							
BI	0.625						
EE	0.57	0.376					
EME	0.627	0.664	0.526				
FC	0.875	0.494	0.43	0.538			
PE	0.416	0.726	0.321	0.467	0.336		
SI	0.513	0.657	0.404	0.615	0.406	0.633	

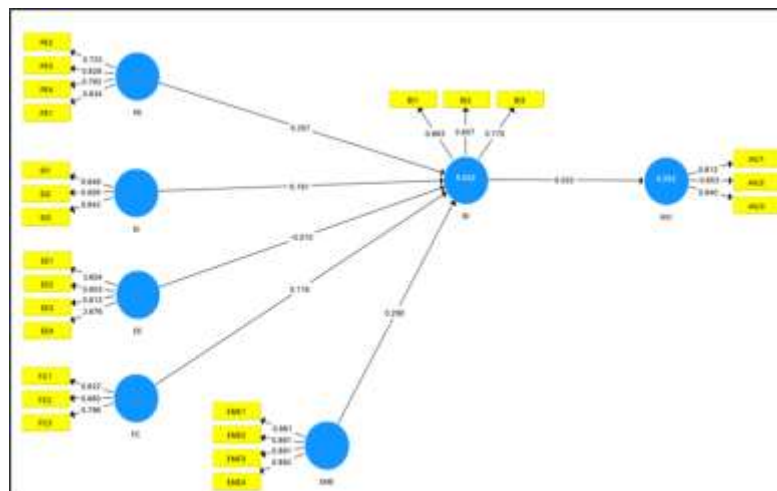


Figure 2: Output of Measurement Model

4.4 Assessment of Structural Model

After confirming the validity and reliability of the constructs, the structural model assessment was performed to examine the relationship between constructs that were hypothesized in the research model. According to Hair et al. (2021), the assessment of structural model involves five steps namely: (1) collinearity and normality assessment among the constructs, (2) structural model path coefficient and Mediation Relation (3) coefficient of determination (R^2 value), (4) effect size f^2 , and (5) predictive relevance Q^2 and blindfolding.

4.4.1 Collinearity Assessment

The structural model was first assessed for collinearity issues using tolerance and variance inflation factors (VIFs). The recommended tolerance level used in the predictors for PLS-SEM is above 0.2 and lesser than 5.0 for VIFs. This is to ensure that the structural model is free from collinearity issues. If collinearity is detected in the structural model, the effected constructs must be combined or deleted from the research model. Table 5 presents the VIF and tolerance of study variables.

Table 5: VIFs for Collinearity Evaluation of the Structural Model

Variables	AIU	BI
BI	1	
EE		1.366
EME		1.756
FC		1.324
PE		1.416
SI		1.67

Note: Performance Expectancy (PE); Effort Expectancy (EE); Facilitating Condition (FC); Social Influence (SI); Emotional Expectancy; Actual Artificial Intention Use (AIU); Behavioural Intention (BI)

4.4.2 Normality Assessment

The normality test of the data was performed even though PLS-SEM does not assume data normality. Analysis to establish skewness and kurtosis of the main constructs was performed to indicate the conformity of the data to normality. It was also performed to confirm that the data is not too far from normality as extremely non-normal data could cause problems in the assessment of the significance of

parameters. Extreme non-normal data can be detected when the values of skewness and kurtosis are greater than 2.828 and 12 respectively (Hatem et al., 2022). As PLS-SEM discard the assumption of normality, the use of the statistical tool of PLS-SEM for further data analysis was supported.

Table 6: Skewness and Kurtosis of Main Variables

Variable	Excess Kurtosis	Skewness
PE1	-0.230	-0.248
PE2	-0.343	-0.342
PE3	-0.471	0.053
PE4	-0.078	-0.438
EE1	-0.342	-0.417
EE2	-0.026	-0.349
EE3	-0.067	-0.427
SI1	2.700	-1.944
SI2	2.330	-1.571
SI3	2.742	-1.685
SI4	1.171	-1.331
FC1	0.442	-0.801
FC2	-0.143	-0.699
FC3	-0.287	-0.491
FC4	-0.833	-0.231
AIU1	0.980	-1.098
AIU2	0.225	-0.884
AIU3	0.497	-0.928
AIU4	0.516	-0.951
EME1	0.675	-0.984
EME2	0.159	-0.888
EME3	-0.243	-0.617
BI1	0.460	-0.628

BI2	-0.406	-0.380
BI3	-0.409	-0.471
BI4	0.077	-0.723

Note: Performance Expectancy (PE); Effort Expectancy (EE); Facilitating Condition (FC); Social Influence (SI); Emotional Expectancy; Actual Artificial Intention Use (AIU); Behavioural Intention (BI)

4.4.3 Multi-Variate Normality Assessment

This study assessed the multivariate skewness and kurtosis using the software available at: <https://webpower.psychstat.org/models/kurtosis/results.php?url=fb9771ad65087c96bda313929fa338>. The results showed that the data collected was not multivariate normal, Mardia’s multivariate skewness ($\beta = 7.41$, $p > 0.05$) and Mardia’s multivariate kurtosis ($\beta = 79.05$, $p > 0.05$), thus this study proceeded to use Smart PLS which is a non-parametric analysis software.

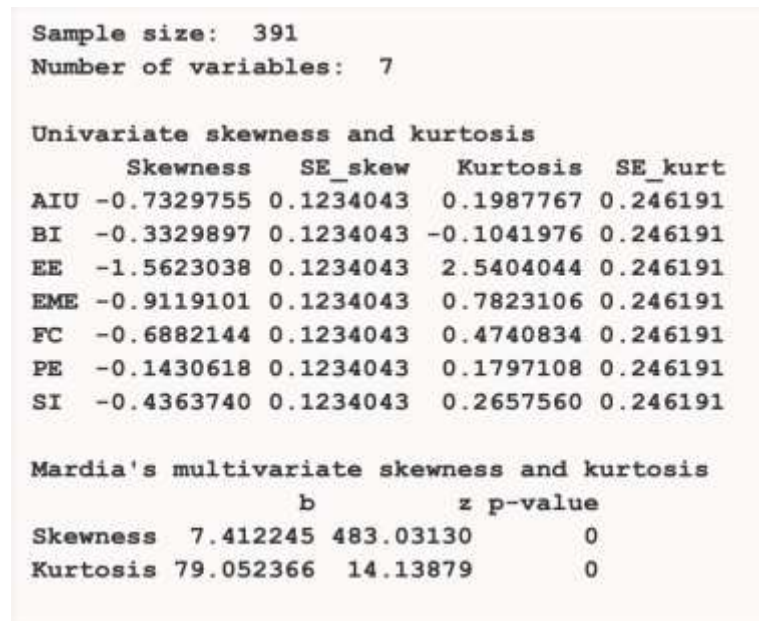


Figure 3: Multivariate Normality Assessment (Source: Web power)

4.4.4 Structural Model Path Coefficient

In the research model, the next step is to assess the structural model by using the path coefficient. The significance of the path coefficient was determined by comparing the t- values to the critical t-values for significance levels of 0.01, 0.05, and 0.10 Bootstrapping was used to compute the empirical t-value for the significance of path coefficients using 1000 subsamples (Ramachandran & Tsokos, 2020). Table 7 tabulated the path coefficients obtained from the analysis to assess the statistical significance in the structural model. The results of the hypothesis showed that all the hypotheses were accepted except H2, the relationship between effort expectancy and Behavioural intention is not accepted due to negative path coefficient and low t values and high p values.

Table 7: Results of Structural Model Analysis (Direct Hypothesis)

Hy p	Path	Beta	Standard Error	T Values	P Values	5.00%	95.00 %	Decision
H1	PE -> BI	0.357	0.045	7.931	0.000	0.267	0.441	Supported
H2	EE -> BI	0.010	0.038	0.252	0.801	0.082	0.065	Not Supported
H3	SI -> BI	0.161	0.049	3.279	0.001	0.061	0.259	Supported
H4	FC -> BI	0.116	0.042	2.739	0.006	0.029	0.201	Supported
H5	EME -> BI	0.290	0.055	5.242	0.000	0.181	0.392	Supported
H6	BI -> AIU	0.502	0.038	13.110	0.000	0.426	0.583	Supported

Note: Performance Expectancy (PE); Effort Expectancy (EE); Facilitating Condition (FC); Social Influence (SI); Emotional Expectancy; Actual Artificial Intention Use (AIU); Behavioural Intention (BI)

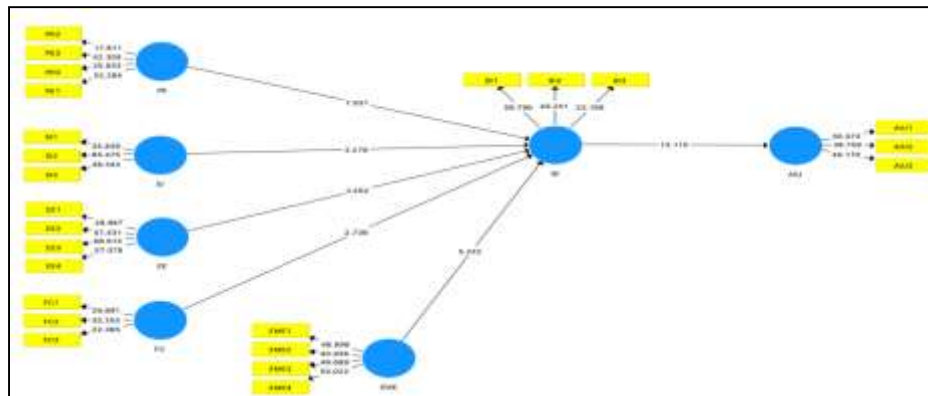


Figure 4: Output of Structural Model

4.5 Variance Explained (R^2)

In PLS, the main evaluation criterion for the goodness of the structural model is that the R^2 measures the coefficient of determination and the level of significance of the path coefficient (beta value). Recommended value for R^2 is between 0.02-0.12 weak, 0.13-0.25 moderate, and 0.26 and above substantial. However, (Hair & Alamer, 2022) qualified these figures and suggested that high R^2 is dependent on specific research context. The R^2 value for endogenous construct behavioural intention and actual use of artificial intelligence is given below. Table 8 presents the values of variance explained.

Table 8: Variance Explained (R^2)

Variable	R Square	R Square Adjusted
AIU	0.252	0.25
BI	0.502	0.495

Note: Actual Artificial Intention Use (AIU); Behavioural Intention (BI)

4.6 Effect Size (f^2)

The study estimated the effect size of all the variables, both statistical significance (P -value) and substantive significance should be reported in study results (Hair & Alamer, 2022), suggesting a change in R^2 should be examined when an exogenous variable is omitted from the model to calculate the effect size (f^2) which explains the substantive impact of the omitted variable on endogenous variables. Commonly used guidelines for effect size were given which is 0.02, 0.15, and 0.35 representing small, medium, and large effects respectively. However, researchers concluded that a variable obtained small effect size does not mean that the variable is unimportant. They also concluded that researchers should carefully estimate the effect size based on their knowledge and the method used for study rather than just comparing it with the given standard values (Serdar et al., 2020; Katebi et al 2021; Lakens, 2022). Table 9 represents the effect size of all exogenous variables of the study.

Table 9: Effect Size of the Study Variables

Construct	Effect Size	
	AIU	BI
BI	0.338	
EE		0.000
EME		0.096
FC		0.021
PE		0.181
SI		0.031

Note: Performance Expectancy (PE); Effort Expectancy (EE); Facilitating Condition (FC); Social Influence (SI); Actual Artificial Intention Use (AIU); Behavioural Intention (BI)

4.7 Predictive Relevance (Q^2)

The predictive accuracy of the model was assessed by using R^2 . In addition, Stone-Geisser's Q^2 value can actually be used to determine the model's predictive relevance. When the value of Q^2 is greater than zero, it indicates that the model has accurately predicted the data points of the endogenous constructs ((Hair & Alamer, 2022)). To obtain Q^2 , blindfolding in Smart-PLS was performed. The blindfolding procedure was performed by omitting every sixth data point in the endogenous construct's indicators and using construct cross-validated redundancy. The omitted data points were then treated as missing data in Smart-PLS. The difference between the omitted data points and the predicted ones were used for calculating the Q^2 (J. J. F. Hair et al., 2014). The Stone-Geisser's Q^2 values are shown in Table 10.

Table 10: Predictive Relevance (Q^2)

Variables	SSO	SSE	$Q^2 (=1-SSE/SSO)$
AIU	1173	975.049	0.169
BI	1173	778.602	0.336
EE	1564	1564	

EME	1564	1564
FC	1173	1173
PE	1564	1564
SI	1173	1173

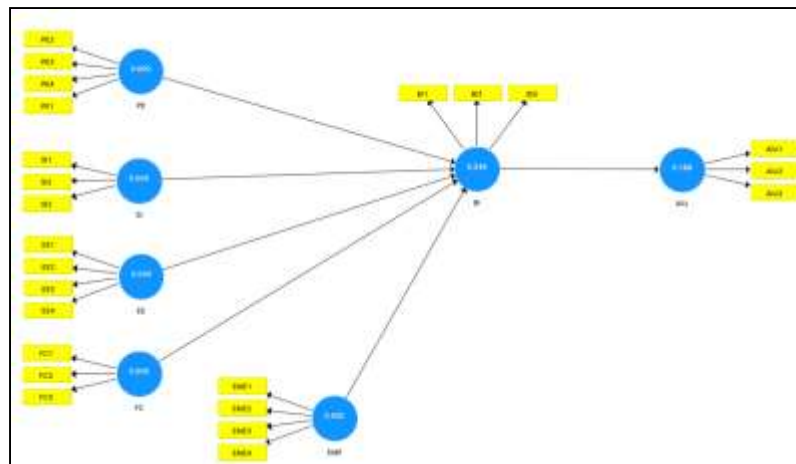


Figure 5: Predictive Relevance of the study (Blindfolding)

The framework suggested in this study has as its theoretical basis the UTAUT theory. The UTAUT incorporates two main dependent variables, namely, i) the behavioural intention to use AI services technology. The independent variables considered in this research are performance expectancy, effort expectancy, social influence, facilitating conditions (based on the UTAUT framework), as well as e-Emotional Expectancy. In addition, behavioural intention is used as an explanatory variable for actual adoption. The various hypotheses defined and discussed below are grouped according to the relevant variables.

Performance Expectancy (PE) – H1

The study confirms that performance expectancy significantly influences behavioral intention (BI) to use AI services ($\beta = .357, p < .05$). This suggests users believe AI services enhance productivity and task performance, aligning with the definitions by Chen et al. (2020) and Davis. The inclusion of sub-variables like extrinsic motivation and relative advantage reinforces the perception of AI as beneficial. This finding supports previous research and highlights PE as a strong predictor of AI adoption.

Effort Expectancy (EE) – H2

Effort expectancy was found to have no significant influence on behavioural intention ($\beta = .010, p > .05$). This result, while not statistically strong, suggests that ease of use alone may not drive AI adoption, particularly among users who already have digital experience. It indicates that users who perceive AI as complex may still avoid it, even if they recognize its potential.

Social Influence (SI) – H3

Social influence has a positive but statistically insignificant effect on BI ($\beta = .161, p > .05$). While peers and social connections may affect perceptions, this study suggests that peer usage alone is not a strong determinant of AI adoption. Nevertheless, the findings are consistent with prior literature Chen et al. (2020), that acknowledges the role of social norms, especially in technologically advanced environments.

Facilitating Conditions (FC) – H4

Facilitating conditions showed a significant positive effect on BI ($\beta = .116, p < .05$). This indicates that access to necessary resources, knowledge, and technical support can boost users' willingness to adopt AI. However, the study notes a possible overestimation of self-perceived capabilities, which might not always translate into actual usage.

Emotional Expectancy (EME) – H5

Emotional expectancy was found to be a significant predictor of BI ($\beta = .290, p < .05$), highlighting the emotional appeal and satisfaction users associate with AI services. This supports the notion that positive emotional experiences encourage adoption, in line with studies by Gansser & Reich (2021) and Kelly et al. (2022).

Behavioural Intention to Use AI – H6

The study concludes that behavioural intention has a significant impact on actual usage of AI technology ($\beta = .038, p < .05$). Although the effect size is modest, it confirms that users with stronger intentions are more likely to adopt AI, consistent with findings by Lavidas (2024). However, the potential for self-reporting bias is acknowledged, emphasizing the need to distinguish between intention and actual usage.

Overall, the findings suggest that performance expectancy, facilitating conditions, emotional expectancy, and behavioural intention are key drivers of AI adoption. In contrast, effort expectancy and social influence had limited statistical significance, possibly due to user familiarity with technology or other contextual factors. These results provide valuable insights into factors influencing AI acceptance and usage and can guide strategies for more effective AI implementation.

5 Conclusion

This study set out to examine the factors influencing the behavioral intention to adopt AI services in Nigeria using a modified UTAUT model. The aim was not only to validate the applicability of UTAUT in a developing country context but also to explore potential modifications that better align with user behavior in Nigeria. The findings confirm that PE and Internet Trust emerged as the most influential predictors of intention to use AI services, reinforcing the importance of perceived usefulness and the reliability of internet-based systems in shaping user attitudes. FC and SI were also found to have a positive influence on behavioral intention, though the impact of SI was not statistically significant, these results indicate that the availability of supportive infrastructure, resources, and encouragement from peers or social groups play a critical role in the decision to adopt AI technologies. However, EE a core construct in the original UTAUT model did not significantly impact behavioral intention in this study. This deviation suggests that for Nigerian users, ease of use may not be a primary concern when considering AI adoption, possibly due to growing digital literacy or increased exposure to technology. This finding contradicts several earlier studies but aligns with recent arguments that emotional engagement and trust in the system are becoming more prominent determinants in technology acceptance. To account for this, the study proposes the incorporation of Emotional Expectancy as an extension to the UTAUT framework, especially in emerging economies. Emotional responses to AI, including excitement, fear, or curiosity, may influence user behavior more than cognitive evaluations like effort, especially in culturally diverse or technology-developing contexts. From a practical perspective, the results provide guidance for technology developers, policymakers, and educators. To enhance AI adoption, it is vital to strengthen trust in online systems through robust cybersecurity and data privacy policies; Emphasize the tangible benefits and efficiency gains of AI applications; Provide necessary infrastructure and user support to reduce access barriers; Leverage influential social groups or communities to encourage adoption. Theoretically, the study contributes to ongoing debates about the adaptability of UTAUT in non-Western contexts and supports the idea that context-specific constructs such as internet trust and emotional factors are critical to fully understanding technology adoption in countries like Nigeria. Future research should explore these alternative constructs further and conduct qualitative investigations to deepen understanding of users' emotional and contextual motivations. Additionally, longitudinal studies could assess how these factors evolve as AI services become more widespread. In conclusion, this study affirms the relevance of the UTAUT model while emphasizing the need for contextual refinement. By acknowledging both universal and local factors, we can develop a more accurate and culturally sensitive framework for understanding AI adoption in developing economies.

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