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# EXAMINING UNDERGRADUATES' PERCEPTIONS OF CHATBOTS IN LEARNING: AN INTEGRATION OF TECHNOLOGY ACCEPTANCE MODEL WITH THE VALUE-BASED ADOPTION MODEL

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# EXAMINING UNDERGRADUATES' PERCEPTIONS OF CHATBOTS IN LEARNING: AN INTEGRATION OF TECHNOLOGY ACCEPTANCE MODEL WITH THE VALUE-BASED ADOPTION MODEL

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***Abstract***

With the continuous advancements in technology, chatbots are poised to play an increasingly crucial role in education. This study aims to explore how undergraduates perceive chatbots for learning activities. The study investigated the interconnected dynamics between Technology Acceptance Model (TAM) and Value-Based Adoption Model (VAM) constructs, which include perceived enjoyment, perceived risk, and perceived value. These factors are examined to predict the attitudes of undergraduates and their acceptance of chatbots for higher education learning experiences. A survey involving 365 participants was conducted, and the hypotheses were assessed using Structural Equation Modeling (SPSS-AMOS). The study underscores the primary factors influencing chatbot acceptance among undergraduates, including perceived ease of use, perceived usefulness, attitude, and perceived value. It is noteworthy that perceived risk and perceived enjoyment did not play a significant predictor of students' attitudes and their acceptance of chatbots for learning. It is therefore recommended that higher institutions of learning and technology developers customize the chatbot applications to meet the needs and preferences of students and promote the integration of chatbot technology in supporting learning within the higher education landscape of Nigeria.

## Introduction

The term "Chatbot" is a combination of "chat" and "robot." It uses natural language for input and artificial intelligence to simulate interpersonal conversations or chat interactions as output software (Reshmi & Balakrishnan, 2016). Chatbots execute voice conversations or text messages through software-built commands. ELIZA, developed by Joseph Weizenbaum at the Massachusetts Institute of Technology (MIT) in 1966, is the world's first chatbot (Weizenbaum, 1966). During the 1980s, chatbots were primarily designed for the gaming industry and were employed to assess whether individuals could distinguish them from humans (Bächle et al., 2018). ELIZA is one of the initial Turing-tested chatbots globally and was designed in natural language and mainly used in the medical field. It searches a database for keywords in the user's question, matches these keywords with corresponding patterns, and ultimately outputs the matching answer. ELIZA has been applied in the mental health sector, guiding patients to interact with the system to obtain treatment-related information and providing auxiliary support for mental health care. The software learns to emulate human-like emotions and simulate situational conversations between a psychiatrist and a patient (Adamopoulou & Moussiades, 2020), marking the beginning of the era of intelligent chatbots. The evolution of artificial intelligence, marked by advancements in natural language processing, speech recognition, deep learning, and pattern recognition, has propelled the continuous development of chatbot systems. This has resulted in significant changes in the method of human-computer interaction, establishing a foundation for the integration of information science into the machine-learning era.

Chatbots have become increasingly popular across various service platforms. They allow the introduction of integrated services and exploring new topics. The ability of communication software to adapt to different platforms has attracted more companies and software engineers to adopt and develop chatbots. This has resulted in enhanced stability, ease of use, and user engagement. In recent years, chatbots have become commonly used tools in daily life due to the high usage rate of communication software and the rapid development of artificial intelligence technology. Chatbots aim to create realistic human-like interactions with their constant updates, unlimited memory, instant actions, and 24/7 availability. They offer features such as self-containment, constant activity, and the ability to track users' preferences, interests, and socio-demographics. Chatbots serve as customer service agents by providing personalized interactions, and enhancing satisfaction and engagement (Alt et al., 2021). They streamline customer service processes by providing real-time information and order placement such as news, weather updates, navigation, and various services such as room reservations, ticket bookings, online shopping, and meal ordering. Chatbots are easier and more cost-effective to develop compared to websites and apps (Ashfaq et al., 2020; Nichifor et al., 2021). Beyond offering uninterrupted service and reducing labor costs for enterprises, they provide a technological trend.

Chatbots can be divided into two primary categories: task-oriented and non-task-oriented (Hussain et al., 2019). Task-oriented chatbots are designed for specific functions and domain-based conversations such as making reservations, booking flights, placing online orders, and providing specific information. However, task-oriented systems have a limitation in their ability to extend beyond the programmed topic scope. On the other hand, non-task-oriented chatbots engage in entertaining conversations across various domains in an unstructured manner (Hussain et al., 2019; Justo et al., 2021). As chatbots mimic human-to-human interaction, they are often perceived as anthropomorphic (Seeger et al., 2018), representing a prominent example of intelligent human-computer interaction. According to Youn and Jin (2021), chatbots have the potential to extend beyond mechanically intelligent AI to incorporate analytical, intuitive, and empathetic capabilities. Mechanical chatbots provide predefined responses, analytical chatbots analyze problems, intuitive chatbots understand complaints contextually, and empathetic chatbots recognize and understand users' emotions.

Various studies have shown that chatbots tend to perform better when they are created explicitly for a certain sphere or group. These chatbot applications can be found in various sectors, including education, business, e-commerce, communication, marketing, news, health, design, food, finance, entertainment, travel, utilities, and more (Adamopoulou and Moussiades, 2020). However, while chatbots are becoming increasingly human-like, their usage still has some drawbacks. For instance, some people may be reluctant to interact with impersonal machines instead of humans (Nichifor et al., 2021). Furthermore, there are concerns about privacy and security, as human hackers could exploit the chatbot's features. Additionally, chatbots programmed with natural language processing may lack intuitive interactions, leading to errors and a perceived absence of human emotions, engagement, and personality. Users may find receiving personalized feedback from chatbots in certain situations uncomfortable, as they may perceive them as immature technology (Smutny and Schreiberova, 2020). Interacting with chatbots, particularly when a user is already dissatisfied, may hurt the brand or organization's service value (Hildebrand and Bergner, 2019). A lack of knowledge about chatbots could contribute to user discomfort, resulting in a reluctance to engage in interactions. Additionally, fears of losing autonomy, technical apprehensions, and perceptions of low usefulness could lead to resistance and avoidance (Da Paixão Pinto et al., 2021). Despite their organizational benefits, various factors can impede effective communication between chatbots and users, including chatbot features and user perceptions (e.g., technological experience, the need for natural conversation, and perceived usefulness).

**Chatbots in Education**

Chatbots have been successfully used in various fields for military, legal, business, and education. In educational contexts, chatbots have gained popularity due to their ability to mimic human discussions, automate educational services, and alleviate the workload of teachers (Okonkwo & Ade-Ibijola 2021). The application of chatbots in education has become a trend in recent years and it’s been used as an auxiliary learning tool (Smutny & Schreiberova, 2020). In recent years, there have been several educational applications of chatbots, indicating their potential to enhance learning outcomes (Winkler & Söllner, 2018). However, their utilization to assist teaching is still in its early stages (Smutny & Schreiberova, 2020). The increasing student-to-teacher ratio, influenced by distance education and massive open online courses (MOOCs), coupled with the challenges posed by the COVID-19 pandemic has made it difficult for teachers to offer individualized support which has resulted in increased dissatisfaction among students and higher dropout rates (Rejón-Guardia, Vich-I-Martorell, 2020). To address these challenges, there has been an accelerated acceptance of chatbots in education, proving to be valuable resources for learners transitioning to remote and online learning. The increasing reliance on mobile technology in education, alongside the widespread availability of messaging applications, positions chatbots as a preferred technological solution for addressing educational challenges (Bahja, Hammad, & Hassouna, 2019). Chatbots play a crucial role in assisting students beyond the traditional classroom setting. They can aid in tasks such as course registration, provide personalized feedback on assignments, and offer round-the-clock technical and learning support (Kuhail, Alturki, Alramlawi, Alhejori, 2023). Integrating courses into the chatbot framework allows students to go beyond one-sided learning in the classroom, and when combined with mobile devices, the chatbot serves as an auxiliary teaching tool, ensuring a more diverse and comprehensive teaching approach.

The use of chatbot technology in education has become a valuable resource, involving students as advisors, tutors, classmates, or even gaming partners to boost cognitive skills, motivation, and overall learning performance (Fidan & Gencel, 2022; Pérez-Marín, 2021, Sriwisathiyakun, & Dhamanitayakul, 2022). Learning environments based on chatbots empower students to assume control over their education by breaking down learning components and offering continuous assistance and feedback. This personalized approach enables learners to efficiently acquire knowledge and skills. Chatbots also foster collaborative learning, facilitating resource sharing among users irrespective of geographical location or time zone, resulting in a more personalized educational experience tailored to individual learning styles. Learners can evaluate their behaviour, monitor progress, and develop metacognitive learning skills (Al-Abdullatif, 2023).

Chatbots play a crucial role in facilitating mobile learning, allowing students to access learning materials at any time and from anywhere, making them a valuable tool for ubiquitous learning. They can creatively administer exams, evaluations, and feedback that align with the physical properties of mobile devices, prompting swift interaction with learning content and providing prompt feedback. Likewise, chatbots stimulate higher-order thinking, nurture self-efficacy in learning, promote effective self-management, and enhance self-regulation in learning (Pérez-Marín, 2021; Park, et.al, 2019). The adoption of educational chatbots holds transformative potential, with the capacity to revolutionize both learning and teaching, aiding educational institutions in adapting to the dynamic landscape of modern education.

Chen et al. (2020) employed chatbots for Chinese single-word learning and found an improvement in students' performance. The study suggested that employing chatbots in one-on-one personal tutoring achieved better learning outcomes compared to using them in many-to-one classrooms. Pham et al. (2018) developed a chatbot to aid users in practicing English, incorporating functions such as general greetings, sending reminders, responding to specific requests and explaining learning content. The chatbot created a pleasant atmosphere for students, effectively capturing their attention. Furthermore, chatbots were observed to aid students facing difficulties, enabling rapid progress in studies and reducing the gap between mainstream and minority students. Suitable chatbots were found to have positive effects on student influences. Xu et al. (2021) developed a robot that reads with children, with the chatbot expanding and extending sentences based on children's dialogue during training. The experimental results demonstrated that a guided robot improved children's reading comprehension, leading to the ability to express more understandable sentences after interaction with the chatbot.

Hobert and Meyer (2019) designed a chatbot to serve as a teaching assistant for programming instruction. This chatbot could answer open-ended questions, automatically evaluate user-submitted programs, and use natural language to guide users through exercises. Bailey et al. (2021) also developed a chatbot for interacting with students and sharing story content to support language learning. The experimental results revealed a positive correlation between chatbot interaction and self-confidence, with students exhibiting high self-confidence demonstrating a willingness to work hard and invest more time in their studies. Hwang and Chang's research (2021) highlighted the previous uses of chatbot education. The study suggested designing chatbots for different learning activities, enabling students not only to complete tasks but also to interact with classmates, thereby creating a more interactive learning space.

**Research Model and Hypothesis Development**

Several studies have been conducted to assess university students' perceptions of chatbot technology in higher education. These studies have been conducted in various learning contexts, with a significant focus on language learning and online learning (Chen, et al., 2020; Beldo-Medina & Calvo-Ferrer, (20220; Huang et al., 2021; Fidan & Gencel, 2022). The results indicate that students are highly willing to embrace chatbots and demand their integration into learning. Chatbots have been utilized as teaching agents to aid student learning and have been evaluated using theoretical models of technological acceptance, such as the Technology Acceptance Model (TAM), its extended forms (extended TAM), and both the Unified Theory of Acceptance and Use of Technology (UTAUT) and its updated version (UTAUT2). Results consistently show a high level of technological acceptance among university students regarding the adoption and use of chatbot technology in learning. Several factors have influenced this acceptance, such as personalized learning experiences, self-efficacy, accessibility, availability, trust, perceived risk, interaction, prompt feedback, user-friendliness, attitude, and enjoyment (Chang et al., 2021; Winkler & Söllner, 2018; Sriwisathiyakun & Dhamanitayakul, 2022; Keong, 2022; Pillai, 2023; Chatterjee & Bhattacharjee, 2020; Okonkwo & Ade-Ibijola, 2021; Keong, 2022). Overall, these studies suggest that students view chatbots as smart tools that can improve their academic performance.

**Technology Acceptance Model**

The Technology Acceptance Model (TAM) developed by Davis (1985), explains how people accept or reject technology. It suggests that users' perceived usefulness and ease of use are the primary factors that influence their acceptance (Davis et al., 1989). These factors directly affect a user's attitude, which is the third component of the TAM. Attitude serves as a significant factor in predicting users' acceptance and adoption behavior toward technology. According to Park (2009), these three factors significantly predict users' willingness to use technology.

**Value-Based Adoption Model**

The Value-Based Adoption Model (VAM) proposed by Kim et al. (2007) is an extension of the TAM that addresses its limitations in predicting individuals' decision-making processes related to new technology (King & He, 2006). The VAM incorporates the concept of perceived value and emphasizes the significance of perceived value as a potent predictor of usage intentions and acceptance. In the context of technology use intention, perceived value is predicted by two primary determinants: the benefits (usefulness and enjoyment) that individuals derive and the relative sacrifices (perceived risk) that they perceive (Kim et al., 2017). In this study, perceived value represents undergraduates' evaluation of the balance between perceived advantages and potential risks associated with the utilization of chatbots. If undergraduates perceive chatbots as enhancing their learning experience (valuable), they are more inclined to accept and adopt them.

**Integrated Model: Technology Acceptance Model (TAM) and Value-Based Adoption Model (VAM) for Chatbot Acceptance**

According to Kim et al. (2017), integrating the Technology Acceptance Model (TAM) and the Value-Based Adoption Model (VAM) provides a comprehensive representation of the decision-making process for new technology adoption. VAM is the most effective model in predicting users' acceptance and adoption of AI (Sohn & Kwon, 2020). Several studies have integrated VAM with other models to investigate technology adoption in different contexts (Kim et al., 2017; Kim et al., 2019; Hsiao & Chen, 2017; Liao et al., 2022; Liang et al., 2021). Recent studies on educational chatbots have investigated students' acceptance of chatbot technology in learning, with a focus on models such as the TAM, UTAUT, and UTAUT2. The Value-Based Adoption Model (VAM) has received limited attention. The VAM incorporates factors such as perceived benefits, perceived enjoyment, perceived risks, and overall perceived value. Integrating these factors with TAM can offer a more comprehensive understanding of undergraduates' acceptance of chatbots in learning Al-Abdullatif (2023). This study proposes an integrated model that combines elements from TAM with VAM to assess chatbot acceptance among undergraduates.

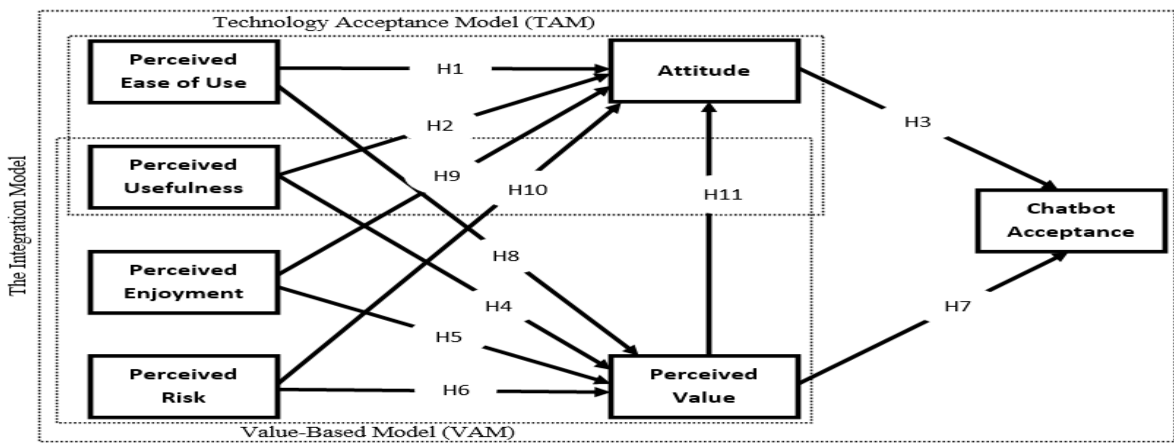


Figure 1: Study's research model

**Theoretical Framework/Relationship in the Proposed Model**

**Relationship in TAM**

TAM is the primary model to examine students' perceptions of chatbot use in learning (Liao et al., 2022). Perceived ease of use refers to how easy it is to interact with the chatbot, while perceived usefulness refers to the degree to which chatbot technology enhances the learning experience. Attitude is the student's opinion about integrating chatbot technology into the learning process. Studies show that perceived ease of use and usefulness are critical factors that positively influence students' attitudes toward adopting chatbots in learning (Kumar & Silva, 2020; Chocarro et al., 2021; Aslam et al., 2022; Darayseh, 2023). Students' attitudes toward chatbots are also a significant predictor of their acceptance and usage behavior (Okonkwo &Ade-Ibijola, 2021; Keong, 2022).

Therefore, this study aimed to examine factors that influence undergraduates' perception of chatbots in learning by investigating the following hypotheses.

$H_1$: Perceived ease of use has a positive effect on undergraduates' attitudes toward using chatbots in learning.
$H_2$: Perceived usefulness has a positive effect on undergraduates' attitudes toward using chatbots in learning.
$H_3$: Attitudes have a positive effect on undergraduates' acceptance of using chatbots in learning.

**Relationship in VAM**

The Value-Based Adoption Model (VAM) focuses on the importance of perceived benefits in accepting new technology (Kim et al., 2007). Perceived benefits encompass two crucial factors: perceived enjoyment and perceived usefulness. In the use of chatbots, perceived usefulness refers to how students believe interacting with them can positively impact their learning performance. This can include better communication with teachers, improved comprehension, and increased engagement with learning materials. Yu et al. (2017) and Liao et al. (2022) suggest that perceived usefulness and perceived value are the key factors in the adoption of media tablets and e-learning systems., while similar findings are reported in the studies of Kim et al. (2019). Hence, the following hypothesis was proposed:

$H_4$: Perceived usefulness has a positive effect on undergraduates' perceived value of using chatbots in learning

Further, perceived enjoyment strongly influences perceived value, contributing to the prediction of technology adoption (Kim et al., 2007). Chatbots offer exciting and enjoyable benefits to students, enhancing their learning experience. In this study, perceived enjoyment refers to the extent to which students consider the use of chatbots as an interesting and delightful learning experience. Chatbots can motivate students and improve learning outcomes by providing an enjoyable learning experience. Studies show a significant relationship between perceived enjoyment and perceived value (Yang et al., 2016; Chen et al., 2020; Sohn & Kwon, 2020). Hence, the following hypothesis was proposed:

$H_5$: Perceived enjoyment has a positive effect on undergraduates' perceived value of using chatbots in learning
The Value-Based Adoption Model (VAM) cites perceived risks as a key factor in technology adoption, including chatbots. These risks can be monetary or non-monetary, such as concerns about time, effort, security, and privacy, which can affect the perceived value of chatbots (Rapp et al., 2021). Users consider security and privacy risks when interacting with chatbots. These risks may outweigh the potential benefits and discourage adoption (Kim et al., 2017; Liang et al., 2021; Liao et al., 2022). Hence, the following hypothesis was proposed:

$H_6$: Perceived risks negatively affect undergraduates' perceived value of using chatbots in learning.
The perceived value influences the adoption of new technology. According to Kim et al. (2007), Huang et al. (2019), and Sacchetti (2022), Chatbot's perceived value can be improved by students' educational experiences. Based on this, the following hypothesis was proposed:

$H_7$: Perceived value positively affects undergraduates' acceptance of using chatbots in learning

**The Relationship of TAM and VAM**

A chatbot's ease of use affects its perceived value to students. An easy-to-use chatbot saves time and effort, making it more convenient for students to use. Studies show that an easy-to-use chatbot is more likely to attract and retain students. Based on this, the following hypothesis is proposed:

$H_8$: Perceived ease of use positively affects undergraduates' perceived value of chatbots in learning

The relationship between perceived enjoyment and user attitude towards adopting new technology, specifically chatbots in learning is a significant area of research in technology adoption (Sohn & Kwon, 2019). A positive perception of chatbots as enjoyable and pleasurable enhances students' willingness to adopt and hold a favorable view of this technology, contributing to an enhanced overall user experience. Studies have shown a positive relationship between perceived enjoyment and user attitudes towards accepting chatbot technology. Hence, the following hypothesis was formulated:

$H_9$: Perceived enjoyment positively affects undergraduates' attitudes toward using chatbots in learning

Users' attitudes toward new technologies are influenced by their perception of the risks associated with them (Keong, 2022; Kim & Jim, 2021). This perception is known as perceived risk. Studies have shown that perceived risk has a strong correlation with user attitudes towards accepting new technology Aslam et al., 2021; Chatterjee & Bhattacharjee, 2020; Keong, 2022; Marjerison, 2022; Rapp et al., 2021). When individuals perceive a high level of risk associated with a technology, they may be reluctant to adopt it, resulting in negative opinions about it. This is true for chatbots as well, where increased perceived risks negatively affect user attitudes towards technology use. Therefore, this study presumes the hypothesis has

$H_{10}$: Perceived risks negatively affect undergraduates' attitudes toward using chatbots in learning.

Research suggests that the perceived value of technology is a key factor in user adoption (Yin, 2021; Huang, 2019). Studies have found that users who see higher value in using technology are more likely to have a positive attitude toward it (Kim et al., 2017; Ashfaq et al., 2021; Hsiao and Chen, 2017). Therefore, it is hypothesized that:

$H_{11}$: Perceived value positively affects undergraduates' attitudes toward using chatbots in learning

## Methodology

### Data Collection and Participants

The research employed a descriptive survey research design to investigate the perceptions of undergraduates on the utilization of chatbots in the learning process. The population for this study is all undergraduates in Southwest Nigeria. Participants were reached through an electronic link to the survey questionnaire distributed through email and social networking platforms (WhatsApp and Telegram). The respondents were given four weeks to voluntarily complete and submit their responses via the online survey. The study received 365 complete responses, meeting the sample size criteria recommended by Weisberg and Bowen for social science research (Hill, 1998). Table

1 shows the demographic variables of respondents. Among the participants, 123 (33.7%) were male, and 242 (66.3%) were female, while most of the participants were aged between 19-28 years (74.6%).

**Table1: Demographic variables (N = 365)**

| | Characteristics | N | % |
|---|---|---|---|
| **Gender** | Male | 123 | 33.7 |
| | Female | 242 | 66.3 |
| **Age** | < 18 | 27 | 7.4 |
| | 19-23 | 140 | 38.4 |
| | 24-28 | 132 | 36.2 |
| | 29-33 | 47 | 12.9 |
| | >33 | 19 | 5.2 |

## Measurement

The measurement instrument's item development was adopted from validated past empirical studies and modified to fit the goal of the current study. The Technology Acceptance Model (TAM) constructs were adopted from Davis (1989), and comprised perceived ease of use (4 items), perceived usefulness (4 items), attitude toward using (4 items), and chatbot acceptance (5 items). Additionally, the Value-based Adoption Model (VAM) constructs adopted from Liao et al. (2022), included perceived enjoyment (3 items), perceived risks (3 items), and perceived value (4 items). To ensure clarity and appropriateness, three educational technology professors reviewed and revised all items, resulting in slight modifications to the wording of a few items. The questionnaire consisted of 27 items, and respondents were asked to rate their responses using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items were divided into two sections. Section (A) gathered demographic information from the participants, while section (B) elicited responses on participants' perceptions of the seven constructs as outlined in Figure 1.

## Data Analysis

The data were imported and organized using the Statistical Package for the Social Sciences (SPSS) version 27. Subsequently, structural equation modeling (SEM) with AMOS was employed to test the hypotheses. As outlined by Hair et al. (2017), SEM analysis involves two primary phases: first, assessing the outer model, known as the measurement model, by computing metrics such as factor loadings, internal consistency reliability, convergent validity, and discriminant validity; second, measuring the inner model, referred to as the structural model, which involves hypothesis testing among the model constructs. The SEM analysis findings in this study adhere to the guidelines provided by Hair et al. (2019).

## Result

### Measurement Model Analysis

A Structural Equation Modeling (SEM) with AMOS was employed for analysis. As outlined by Hair et al. (2019), SEM analysis involves two primary phases: first, assessing the outer model, known as the measurement model, by computing metrics such as factor loadings, internal consistency reliability, convergent validity, and discriminant validity; second, measuring the inner model, referred to as the structural model, which involves hypothesis testing among the model constructs.

Confirmatory Factor Analysis (CFA) was computed using AMOS to test the measurement models. The first stage in evaluating the measurement model involved determining the construct validity, which refers to how well the items measure the intended concept. This is achieved by applying four analytical procedures: (1) assessment of item loadings; (2) internal consistency reliability (Cronbach's alpha and composite reliabilities); (3) convergent validity; and (4) discriminant validity. All the items calculated indicator loadings are displayed in Table 2.

**Table 2: Loadings, Reliability and Convergent Validity**

| Latent Variable | Indicators | Item Loading | α | CR | AVE |
|---|---|---|---|---|---|
| Perceived Ease of Use | PEOU 1 | 0.98 | 0.90 | 0.93 | 0.77 |
| | PEOU 2 | 0.99 | | | |
| | PEOU 3 | 0.50 | | | |
| | PEOU 3 | 0.96 | | | |
| Perceived Usefulness | PU 1 | 0.82 | 0.97 | 0.97 | 0.89 |
| | PU 2 | 0.97 | | | |
| | PU 3 | 0.98 | | | |
| | PU 4 | 0.96 | | | |
| Perceived Enjoyment | PE 1 | 0.85 | 0.95 | 0.95 | 0.86 |
| | PE 2 | 0.96 | | | |
| | PE 3 | 0.98 | | | |
| Perceived Risk | PR 1 | 0.53 | 0.75 | 0.71 | 0.46 |
| | PR 2 | 0.63 | | | |
| | PR 3 | 0.84 | | | |
| ATTITUDE | ATT 1 | 0.94 | 0.73 | 0.76 | 0.67 |
| | ATT 2 | 0.91 | | | |
| | ATT 3 | 0.61 | | | |
| | ATT 4 | 0.79 | | | |
| Perceived Value | PV1 | 0.94 | 0.87 | 0.89 | 0.67 |
| | PV 2 | 0.94 | | | |
| | PV 3 | 0.65 | | | |
| | PV 4 | 0.70 | | | |
| CHAT ACCEPTANCE | CA 1 | 0.39 | 0.91 | 0.93 | 0.74 |
| | CA 2 | 1.00 | | | |
| | CA 3 | 0.91 | | | |
| | CA 4 | 0.95 | | | |
| | CA 5 | 0.91 | | | |

**Construct Reliability**

Construct Reliability was assessed using Cronbach's Alpha and Composite Reliability. Cronbach Alpha for each construct in the study was found over the required limit of .70 (Nunnally and Bernstein, 1994). Also, composite reliabilities ranged from 0.73 to 0.97, above the 0.70 benchmark

(Hair et al., 2019). Hence, construct reliability was established for each construct in the study (Table 2).

### Convergent validity

Convergent validity of scale items was estimated using Average Variance extracted. The average variance-extracted values were above the threshold value of 0.50 (Fornell & Larcker,1981) for all the constructs except Perceived Risk. However, since the required CR was well over the required value, it can be concluded that the Perceived Risk is valid. Therefore, the scales used for the study have the required convergent validity (Table 2).

### Discriminant validity

Discriminant validity in the study was assessed using the Fornell and Larcker Criterion. According to the Fornell and Larcker criterion, discriminant validity is established when the square root of AVE for a construct is greater than its correlation with the other constructs in the study (Fornell & Larcker, 1981). As illustrated in Table 3, discriminant validity was established using the Fornell and Larcker criterion indicating that the measurement model is reliable and valid.

**Table 3: Discriminant validity analysis and correlation matrix.**

| | PEOU | PU | PE | PR | ATT | PV | CA |
|---|---|---|---|---|---|---|---|
| PEOU | ***0.879*** | | | | | | |
| PU | 0.861 | ***0.945*** | | | | | |
| PE | 0.619 | 0.616 | ***0.928*** | | | | |
| PR | -1.111 | -1.024 | -0.615 | ***0.65*** | | | |
| ATT | 0.3 | 0.086 | -0.361 | -0.315 | ***0.82*** | | |
| PV | 0.637 | 0.381 | -0.023 | -0.73 | 0.877 | ***0.818*** | |
| CA | 0.603 | 0.328 | 0.041 | -0.692 | 0.696 | 0.91 | ***0.861*** |

The bolded value is the square root of AVE

### Model Fit

The model-fit measures were used to assess the model's overall goodness of fit (CMIN/df, GFI, CFI, TLI, SRMR, and RMSEA) and all values were within their respective common acceptance levels (Ullman, 2001; Hu and Bentler, 1998, Bentler, 1990). As shown in Table 4, the seven-factor model (Perceived Ease of Use, Perceived Usefulness, Perceived Enjoyment, Perceived Risk, Attitude, Perceived Value, Chatbot Acceptance) yielded a good fit (CMIN/df = 2.79, GFI = 0.91, CFI = 0.95, TLI = 0.901, SRMR = 0.64, and RMSEA= 0.6) which suggests that these results manifest that the research model has an acceptable fit over the minimum and maximum limit.

**Table 4: Goodness of Fit Statistics**

| Fit Indices | Recommended value | Obtained Value |
|---|---|---|
| Relative Chi-square (CMIN/df) | <3 | 2.79 |
| Goodness-of-Fit Index (GFI) | >.90 | 0.91 |
| Comparative Fit Index (CFI) | >.90 | .949 |
| Tucker Lewis Index (TLI) | >.90 | .901 |
| Standardized Root Mean Square Residual (SRMR) | <.80 | 0.64 |
| Root Mean Square of Error Approximation (RMSEA) | <.80 | 0.6 |

## Structural Model Assessment

**Table 5: Summary of Hypothesis Testing**

| H | Independent Variable | Path | Dependent Variable | Standardized Estimate | Standard Error | t-value | p-value | Decision |
|---|---|---|---|---|---|---|---|---|
| **H1** | PEOU | → | ATT | 0.625 | 0.061 | 18.158 | *** | Supported |
| **H2** | PU | → | ATT | -0.492 | 0.044 | -22.951 | *** | Supported |
| **H3** | ATT | → | CA | 0.257 | 0.033 | 6.096 | *** | Supported |
| **H4** | PU | → | PV | -0.479 | 0.022 | -39.287 | *** | Supported |
| **H5** | PE | → | PV | -0.074 | 0.021 | -6.035 | *** | Supported |
| **H6** | PR | → | PV | -0.182 | 0.026 | -14.922 | *** | Supported |
| **H7** | PV | → | CA | 0.717 | 0.037 | 16.987 | *** | Supported |
| **H8** | PEOU | → | PV | 0.823 | 0.019 | 67.496 | *** | Supported |
| **H9** | PE | → | ATT | 0.027 | 0.018 | 2.75 | 0.006 | Not Supported |
| **H10** | PR | → | ATT | 0.011 | 0.028 | 0.943 | 0.346 | Not Supported |
| **H11** | PV | → | ATT | 0.198 | 0.045 | 4.931 | *** | Supported |
| **R-Square** | | | | | | | | |
| Attitude | | | | 0.97 | | | | |
| Perceived Value | | | | 0.93 | | | | |
| Chatbot Acceptance | | | | 0.96 | | | | |
| **Model Fit** | | | | | | | | |
| **CMNI/df = 2.81, GFI = 0.90, TLI = 0.91, CFI = 0.94 SRMR = 0.7, and RMSEA = 0.6.** | | | | | | | | |

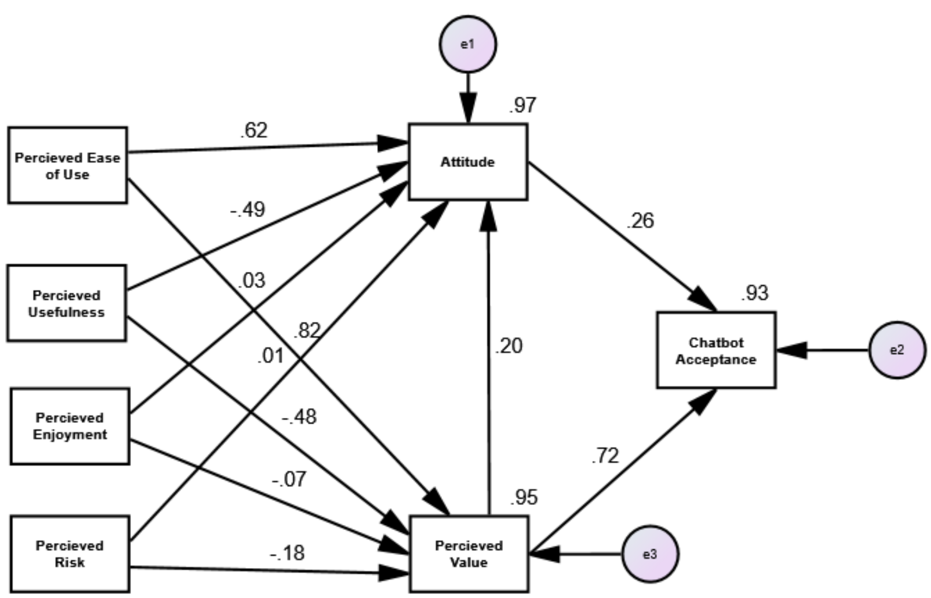


Figure 2: Standardized path coefficient results

A structural equation model generated through AMOS was used to test the relationships. A good-fitting model was accepted if the value of the CMIN/df, the goodness-of-fit (GFI) indices (Hair et al., 2010); the Tucker and Lewis (1973) index (TLI); the Confirmatory fit index (CFI) (Bentler, 1990) is ⩾ 0.90 (Hair et al., 2010). In addition, an adequate-fitting model was accepted if the AMOS computed value of the standardized root mean square residual (RMR) < 0.05, and the root mean square error approximation (RMSEA) is between 0.05 and 0.08 (Hair et al., 2010). The fit indices for the model shown in Table 5 fell within the acceptable range: CMIN/df = 2.8, the goodness-of-fit (GFI) = 0.90, TLI = 0.91, CFI = 0.94, SRMR = 0.7, and RMSEA = 0.6.

Assessment of the structural model involved analyzing the size of standardized path coefficients (β), the standard error (SE), t-values (t), and their respective significance levels (p-values) for each hypothesis, following the guidelines provided by Hair et al (2017) and Hair et al (2019). Results from Table 5 and Figure 2 reveal that the perceived ease of use (β = 0.63, SE = 0.061, t = 18-158, p < 0.001), perceived usefulness (β = -0.492, SE = 0.044, t = -22.951, p < 0.001), perceived value (β = -0.198, SE = 0.045, t = 4.931, p < 0.001) showed a positive effect on undergraduates' attitude towards chatbot for learning, meaning that hypotheses 1,2 and 11 are accepted. However, perceived enjoyment (β = 0.027, SE = 0.018, t = 2.75, p = 0.006) and perceived risk (β = 0.011, SE = 0.028, t = 0.943 p = 0.346) had no positive effect on undergraduate' attitude towards chatbot for learning, thus hypotheses 9 and 10 are rejected.

Furthermore, the result also revealed that undergraduates' perceived value is positively influenced by perceived usefulness (β = -0.479, SE = 0.022, t = -39.287, p < 0.001), perceived enjoyment (β = -0.074, SE = 0.021, t = -6.035, p < 0.001) perceived risk (β = -0.182, SE = 0.026, t = -14.922, p < 0.001) and perceived ease of use (β = 0.823, SE = 0.019, t = 67.496, p < 0.001), therefore hypotheses 4,5,6, and 8 are accepted. As it regards undergraduates' acceptance of using chatbots in learning, the result revealed that both attitude (β = 0.257, SE = 0.033, t = 6.096, p < 0.001), and perceived value (β = 0.717, SE = 0.037, t = 16.987, p < 0.001), had a positive effect on undergraduates' acceptance of using chatbots in learning, therefore accepting hypotheses 3 and 7.

The research model's predictive power was evaluated through the squared multiple correlations ($R^2$) value, as recommended by Henseler et al. (2015). This value represents the variance in the dependent construct explained by the independent constructs. Henseler et al. (2015) categorize $R^2$ values of 0.67, 0.33, and 0.19 as excellent, moderate, and low, respectively, for the dependent construct. The findings of this study indicate that the $R^2$ for attitude (0.95) reveals that 95% of the variance in attitude is explained by perceived ease of use (PEOU), perceived usefulness (PU), perceived enjoyment (PE), perceived risks (PR), and perceived value (PV). Likewise, the $R^2$ for perceived value (0.93) demonstrates that 93% of the variance is accounted for by PEOU, PU, PE, and PR. Similarly, the $R^2$ for chatbot acceptance (0.96) indicates that 96% of the variance is explained by attitude and perceived value. These outcomes show a significantly high predictive ability for all three dependent constructs.

**Discussion and Implications**

The Technology Acceptance Model (TAM) has been extensively employed to explore the factors influencing users' acceptance and adoption of chatbots. Several studies have identified perceived ease of use, and perceived usefulness as significant predictors of users' attitudes and intentions toward chatbot adoption (Aslam et al., 2022; Kim et al., 2021; Goli et al., 2023; Kang et al., 2022;

Alt et al., 2021; Khoa, 2021; Chocarro et al., 2021; Mostafa & Kasamani, 2021; Chen et al., 2020). The study's findings show that perceived ease of use (HI) and perceived usefulness (H2) positively affect undergraduates' attitudes toward using chatbots for learning. This result is consistent with a previous study by Le (2023) which emphasized that perceived usefulness reflects customers' beliefs about an information system's (IS) helpfulness in enhancing performance, while ease of use reflects the extent to which customers believe using an information system is easy and effortless. Kim et al. (2021) found that perceived usefulness predicted attitudes toward chatbots. Goli et al. (2023) and Aslam et al. (2022) reported that perceived ease of use and usefulness significantly influence the continuous usage intention of chatbots. However, some studies present contrasting findings. For example, Chen et al. (2020) found that perceived usefulness was the predictor of behavioural intention, whereas perceived ease of use was not. Additionally, Duan et al. (2023) reported that perceived ease of use had a positive impact on usage intention but no significant impact on usage attitude. These studies suggest that the relationship between perceived ease of use, perceived usefulness, and attitude toward chatbot use for learning may not be consistent across different contexts or user groups. This result emphasizes the importance of designing chatbots that are easy to use, intuitive, and require minimal effort to operate. Higher institutions of learning and instructional designers are to consider the specific needs, and preferences of students and focus on developing appropriate solutions by simplifying the chatbot user interface, providing clear instructions, and offering seamless interactions to enhance ease of use. As technology adoption is constantly evolving, continuous monitoring and adaptation of chatbot functionalities are crucial. Educational institutions should regularly gather feedback from students and educators, assess the performance of chatbots, and implement necessary updates to address emerging needs and challenges. This iterative approach ensures that chatbots remain effective and well-received in supporting the learning process.

The Value-Based Adoption Model (VAM) underscores the influence of perceived enjoyment, perceived value, and perceived risk on users' adoption of technology, such as chatbots. Studies by Yang & Lee (2018) support the multidimensional nature of perceived value, including utilitarian value, hedonic value, and perceived risk. These factors play crucial roles in determining users' repeat purchase intentions in e-commerce and the adoption of virtual personal assistant devices. Rouibah et al. (2021) highlight the impact of perceived risk on adoption behaviour in social commerce and technology acceptance. The findings from this study indicate that perceived enjoyment (H5) and perceived risk (H6) do not significantly affect undergraduates' attitudes toward chatbots for learning, aligning with Gümüş and Çark (2021). However, this contradicts Chao (2019) suggesting varied perspectives on the role of perceived enjoyment. On the other hand, perceived value (H11) positively influences attitudes toward using chatbots for learning, consistent with existing research by Le, (2023) and Yin et al. (2020) emphasizing its impact on intrinsic motivation and adoption decisions. The implication drawn from this finding is that while perceived enjoyment and perceived risk may not significantly influence undergraduates' attitudes toward chatbots for learning, perceived value plays a crucial role in shaping their attitudes and adoption decisions. Therefore, higher institutions of learning and instructional designers should prioritize enhancing the perceived value of chatbots for users, focusing on aspects such as utility, enjoyment, and overall benefits. By recognizing the importance of perceived value, institutions can optimize the user experience, ensuring that chatbots provide meaningful and valuable support in the learning process. Additionally, efforts to educate users about the perceived value of chatbots can contribute to fostering positive attitudes and increased acceptance among students. This can be done by highlighting the benefits and positive impact of chatbots on learning.

Various studies have explored the correlation between undergraduates' perceived ease of use, perceived usefulness, and perceived value. Davis (1989) emphasized the role of perceived ease of use and perceived usefulness as key determinants of user behaviour, indicating the significant impact of these factors on users' perceptions of technology. This is in line with the observation that users' perception of usefulness and ease of use significantly contributes to the value they derive from technology, including chatbots. The findings of the study suggest that chatbots are perceived as valuable learning tools when they are easy to operate. This positive perception is influenced by students' perceived usefulness (H4) and ease of use (H8). Similar to previous studies by Wang (2023), and Guo and Liu (2023), this finding reinforces the notion that perceived usefulness and ease of use contribute to users' perceived value, satisfaction, and intention to use technology. However, Duan et al. (2023) found inconsistent results, as perceived ease of use had no significant impact on perceived value and attitude. Kaur and Bahar (2022) emphasized the importance of undergraduate students' satisfaction with perceived ease of use and usefulness, suggesting that satisfaction levels may influence technology adoption, but not explicitly confirming the positive influence of ease of use and usefulness on perceived value. The study's findings reveal that undergraduates' acceptance of chatbots for learning is positively influenced by students' attitudes (H3) and their perceived value (H7). This aligns with previous research by Okonkwo & Ade-Ibijola, (2021), Darayesh, (2023) on chatbot acceptance and extends our understanding of the influential factors in technology adoption. The identification of perceived value as a significant mediating variable emphasizes its pivotal role in shaping students' attitudes, and consequently, their acceptance and adoption of chatbot use in learning.

## Conclusion and Implication

The integration of the Technology Acceptance Model (TAM) and the Value-Based Adoption Model (VAM) has provided valuable insights into the factors that influence students' attitudes and acceptance of chatbot technology in higher education. This study has identified the key drivers of chatbot acceptance, including perceived usefulness, perceived ease of use, attitude, perceived enjoyment, and perceived value. These insights offer valuable information for educators, policymakers, and technology developers.

The study's findings regarding perceived enjoyment and value contribute to understanding the emotional and practical aspects of chatbot acceptance, providing a nuanced perspective for educators and technology developers to consider. Also, the study's finding that perceived risk did not significantly predict students' attitudes and acceptance of chatbots for learning challenges conventional assumptions about the barriers to technology adoption in educational settings. This calls for further investigation of the factors that contribute to students' perceptions of risk and how these factors may differ in the context of emerging technologies such as chatbots. Overall, the implications of this study highlight the importance of considering multiple dimensions of student perceptions and attitudes when integrating chatbot technology into higher education. By addressing the factors identified in this study, higher institutions of learning and technology developers can better tailor chatbot applications to meet the needs and preferences of students, ultimately enhancing the effectiveness of technology-enhanced learning experiences.

**Recommendations**

The following recommendations are made:

- Higher institutions of learning should promote the integration of chatbot technology in supporting learning within the higher education landscape of Nigeria.
- Educational institutions and instructional designers should prioritize designing chatbots that are easy to use, intuitive, and require minimal effort to operate. This includes simplifying the chatbot user interface, providing clear instructions, and offering seamless interactions to enhance ease of use.
- Higher institutions of learning and technology developers should customize the chatbot applications to meet the needs and preferences of students.
- Educational institutions should regularly gather feedback from students and educators, assess the performance of chatbots, and implement necessary updates to address emerging needs and challenges.

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