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Unlocking Banking Chatbot Adoption: A Unified Approach through Extended TAM and UTAUT Model

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Abstract

This study explores the adoption of chatbots in the banking industry, focusing on users' perceptions and experiences. Facts were collected through surveys using a well-structured questionnaire comprising 108 interrogations covering various aspects of chatbot usage. The survey encompassed dimensions such as perceived enjoyment, perceived risk, self-efficacy, technology anxiety, personal innovativeness, perceived ease of use, perceived usefulness, experience, intention, voluntariness, digital literacy, intention, and adoption. Statistical analyses, including reliability analysis, the chi-square test, and Structural Equation Modeling (SEM), were employed to analyze the data. The adopted models for analysis were TAM and UTAUT. Reliability analysis demonstrated acceptable to excellent internal consistency for most scales. The chi-square test revealed significant relationships between constructs such as perceived ease of use and perceived usefulness of chatbots, voluntariness and personal innovativeness, intention, adoption, and digital literacy. SEM analysis uncovered significant relationships between age and perceived usefulness, digital literacy and adoption or intention, experience and perceived usefulness or ease of use, and voluntariness and ease of use or intention. This study offers valuable insights into chatbot adoption within the banking industry, emphasizing the significance of factors like age, digital literacy, experience, voluntariness, personal innovativeness, and intention in shaping user perceptions and behaviours.

Keywords: Artificial Intelligence, Automation, Banking, Digitalization, Technological Advancement

1. Introduction

The fast-paced advancement of technology is profoundly affecting many industries, and the banking and financial sectors are among those experiencing the most benefit (Sigov *et al.*, 2022). The surge of digitalization has created an unprecedented transformation, introducing newer ways to conduct business and provide services. Artificial Intelligence (AI) and Robotic Process Automation (RPA) stand as key catalysts in this transformative era, especially in the banking and financial services domains (Met *et al.*, 2020). In this evolving landscape, India's banking industry finds itself at a pivotal intersection of technological change and a burgeoning domestic market. In this context, Artificial Intelligence technologies serve as crucial enablers. They guide financial institutions in improving customer experiences, streamlining operations, and skillfully addressing emerging challenges (Pande *et al.*, 2023).

Artificial Intelligence, defined as simulated machine intelligence, comprises computer programs specifically designed to emulate human decision-making processes (Barr & Feigenbaum, 1981). Among AI applications, chatbots are receiving

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considerable attention in the banking sector. These are digital assistants empowered with AI capabilities and natural language processing skills. They are fundamentally altering how customers engage with banking services. Chatbots provide individualized assistance and immediate support and also function as a conduit to an array of banking services. The market has richly rewarded companies that have wisely embraced such groundbreaking technologies, catapulting them to unprecedented levels of success (Singh *et al.*, 2023). Moreover, recent research substantiates the positive influence of chatbots on customer satisfaction and operational efficiency (Chung *et al.*, 2020). Given the compelling advantages, numerous firms have acknowledged the enormous potential of chatbots. Despite the need for substantial time and financial investments for integrating these into existing legacy systems, financial firms are actively moving towards chatbot adoption as a part of their digital transformation strategies.

Thus, the objective of this research is to scrutinize the adoption rate of chatbots in the banking industry, particularly focusing on customer service applications. Second, it explores the customers' experiences, evaluates the usefulness of chatbots, and investigates potential trust issues. The study also delves into the motivations behind banks' decisions to adopt chatbots and the critical factors that drive their successful implementation.

2. Literature Review

2.1 Chatbot as a Technology- AI Companion: Empowering Tech Solutions

The adoption of chatbot technology is mounting in the banking industry, driven by customer acceptance (Alt *et al.*, 2021). Defined as AI-based systems that interact with users through chat or speech interfaces, chatbots perform a range of basic tasks (Nguyen & Sidorova, 2018; Petersson *et al.*,2023). These digital helpers offer a wide array of services in banking at a cost-effective rate, including 24/7 customer support, localized language options, fraud detection, and personalized financial advice (Sayiwal, 2020). However, they also have limitations, such as a restricted scope of questions they can answer, limited language and accent recognition, an inability to handle multiple queries simultaneously, and generally low user awareness (Sayiwal, 2020; Singh & Singh, 2019).

Two prominent models used to understand customer intentions for technology adoption are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models focus on variables like Perceived Usefulness (PU), Perceived Ease Of Use (PEOU), attitudes toward using the system, social influence, and behavioural intentions (Davis *et al.*, 1989; Venkatesh *et al.*, 2003). Previous research that applied TAM and UTAUT to study chatbot usage in banking has produced valuable insights. For example, in Indonesia's banking sector, factors like perceived usefulness, ease of use, innovativeness, and attitudes toward chatbots had a positive impact on behavioural intentions to use the technology (Richad *et al.*, 2019; Singh *et al.*, 2023).

The banking industry is a prominent adopter of emerging technologies, employing a range of digital tools like internet banking, mobile apps, ATMs, and AI-based chatbots to offer a diverse set of services to customers at cost-effective prices (Singh *et al.*, 2023). Despite this, there's a noticeable disparity in the adoption rates of these technologies between developed and emerging economies. Even within a single country, geographical variances exist. Factors such as demographic characteristics strongly influence the adoption of user-friendly, cost-effective technologies like chatbots (Laumer *et al.*, 2019).

Furthermore, positive customer experiences with chatbots have been shown to increase usage rates, though perceived risk factors can negatively impact these rates (Trivedi, 2019). Other research indicates that perceived quality elements like relevancy, pleasure, and trust positively affect customer satisfaction, which in turn boosts technology usage (Liu *et al.*, 2023). Studies also show that performance expectancy and effort expectancy significantly influence chatbot adoption, while social influence has a negligible effect (Silva *et al.*, 2023). Research by Terblanche and Kidd (2022) revealed a direct effect of social influence and

perceived risk on chatbot usage. The UTAUT model further highlights that trust, individual innovation, and attitudes directly affect the intention to use chatbots. Additionally, factors like ease of use, personal innovativeness, performance expectancy, price consciousness, perceived usefulness, and perceived risk have an indirect influence (Kasilingam, 2020).

In delving into the extensive literature on the integration of chatbots within the banking sector, it becomes apparent that initial research predominantly relies on descriptive analyses. However, a notable lack of studies exists in employing a conceptual model to dissect chatbot acceptance and determine the influential factors shaping adoption. Hence, this current study endeavours to bridge this research chasm by constructing a comprehensive conceptual model of technology acceptance. Drawing upon previous investigations pertaining to chatbots' utilization in the banking domain, we aim to elucidate the critical determinants underpinning adoption trends.

2.2 Conceptual Framework Development

In the realm of technology adoption, four primary models have garnered widespread attention for examining user behaviour. The inaugural model, the Theory of Reasoned Action (TRA), was proposed by Fishbein and Azen in 1975. This model eventually evolved into the Theory of Planned Behaviour (TPB), which added perceived behavioural control as a significant determinant influencing behaviours that was later established in a study carried out by Gu *et al.* (2009). The second widely recognized model is the Technology Acceptance Model (TAM), introduced by Davis in 1985. This model was particularly effective, with a 40 percent success rate in predicting system use (Legris *et al.*, 2003). TAM initially postulated that internal features like system capabilities spur user motivation, which in turn acts as a catalyst for broad system use. It initially focused on three key factors: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and the user's attitude toward using the system. This model underwent several enhancements, including the incorporation of external factors like system characteristics, user participation, and training, as well as process implementation (Venkatesh & Davis, 1996).

Most existing research has examined chatbot adoption by considering entire nations as the unit of analysis (Trivedi, 2019; Silva *et al.*, 2023; Liu *et al.*, 2023). Very few studies have focused on specific geographic areas, and these studies often overlook the application of advanced technology adoption models like TAM and UTAUT. This represents a significant gap in the literature.

Building upon this, TAM2 added social influences and cognitive instrumental processes into the mix (Venkatesh & Davis, 2000). The third model is Roger's Innovation Diffusion Theory (IDT) from 1983, which employs five core determinants—relative advantage, complexity, compatibility, trial ability, and observability—to explain adoption behaviour. The fourth model, the Unified Theory of Acceptance and Use of Technology (UTAUT), emerged in 2003 (Venkatesh *et al.*, 2003). This model amalgamates elements of the preceding four theories alongside two motivation models. However, it has faced criticism for neglecting some significant relationships and constructs (Venkatesh & Bala, 2008; Marchewka & Kostiwa, 2007). The study has employed both the TAM and UTAUT model because of their comprehensive nature and extensive applicability in understanding the intricacies of technology adoption behaviour.

The study's conceptual framework leans on two widely recognized theories: The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM provides insights into how users' perceptions of a technology's ease of use and usefulness guide their intention to adopt it. UTAUT further expands upon this foundation by incorporating additional variables like social influence and facilitating conditions. Specifically, for this study, these theories are tailored to focus on elements crucial to the adoption of chatbots in the banking sector. This research is grounded in established theoretical models in the domain of technology adoption, with a particular focus on TAM and UTAUT models. Figure 1 is the proposed model for adoption of banking chatbots. This model serves as valuable frameworks for understanding how users interact with and perceive technologies such as chatbots in the banking environment.

To address this research gap, the present study aims to explore the relationship between customer experiences and chatbot adoption in the banking industry, focusing specifically on the regional context of Coimbatore City. Moreover, this study leverages both TAM and UTAUT models to build robust theories. These models will be tested through a Structured Equation Model, offering a more nuanced understanding of technology adoption behaviour. The study seeks to contribute valuable insights to the field, particularly concerning how location and customer experience interact to influence the successful implementation of chatbot technology in banking. Table 1 lists the constructs adopted in the model, which collectively shape users' behavior and decision-making regarding chatbot usage in banking transactions

2.3 Methods

The Extended Technology Acceptance Model (TAM) has garnered widespread acceptance as a reliable and effective framework applicable across genders, diverse settings, and over time (Cheung *et al.*, 2005; Drennan *et al.*, 2005; Groves & Zemel, 2000; Liaw & Huang, 2003; Pan *et al.*, 2003). This broad acceptance lends strong support to the hypotheses underpinning the constructs investigated in this study. Moreover, the selection of TAM as the theoretical framework stems from its demonstrated efficacy in elucidating the intentions of pre-service teachers to adopt technology (Kiraz & Ozdemir, 2006; Ma *et al.*, 2005; Teo, 2009). The research aims to construct a robust theoretical framework using Structural Equation Modeling (SEM).Top of Form

2.4 Data Nature and Sources

The study sources data from both primary and secondary channels. Secondary data enriches the conceptual framework, furnishes insights into existing models, and reviews findings from previous studies. This data mainly derives from scholarly articles published in academic journals; primary data is collected via a well-designed questionnaire tailored to the study's objectives. The survey method is used for this purpose. The questionnaire consists of 108 items assessing a range of factors connected to chatbot usage. Data gathering is executed through Google Forms and disseminated via email to participants. Primary data is congregated from 195 users engaged in chatbot-driven banking transactions in Coimbatore City, Tamil Nadu. These users are customers of various banks operating in Coimbatore. The study examines the correlation between customer perception and experience concerning chatbot adoption.

3. Results and Discussions

The study employs a mixture of statistical techniques. Collected data are organized into tables, and frequency distribution charts are generated. Data reliability and validity are assessed using Cronbach's alpha (α) reliability test. Subsequently, Chi-square tests are employed to probe relationships between different

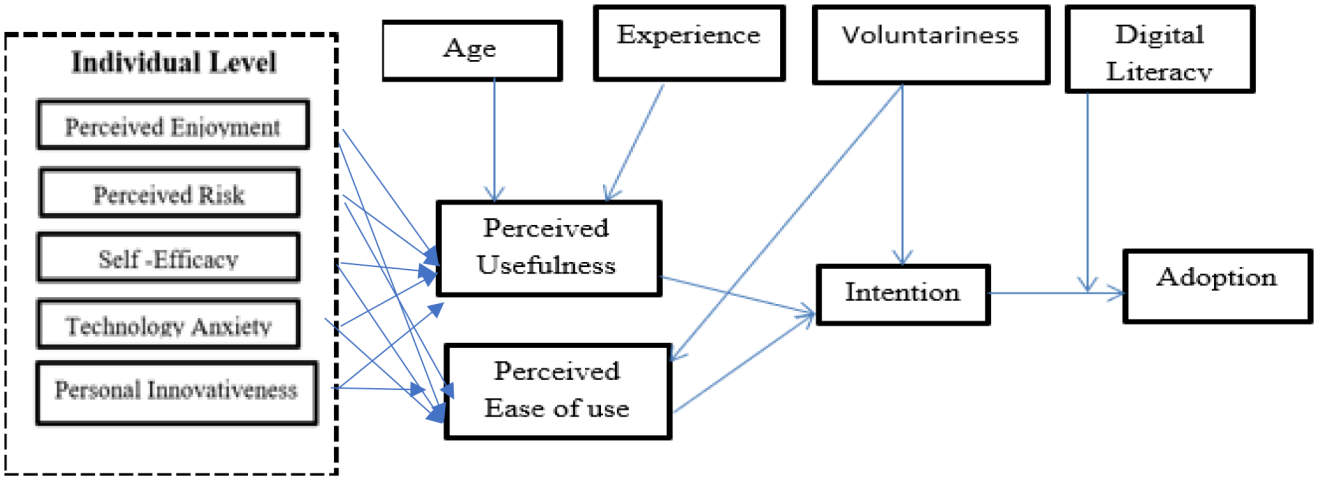


Figure 1. Proposed research model for adoption of banking chatbots.

Table 1. Constructs adopted in the Model

Construct	Definition	Theoretical Background
Perceived usefulness	The degree to which a person believes that using a particular system would enhance his or her job performance.	(Davis *et al.,* 1989)
Perceived ease of use	The degree to which a person believes that using a particular system would be free of effort.	(Davis *et al.,* 1989)
Perceived enjoyment	This refers to the level of enjoyment users feel when using chatbots in banking, which positively influences their intent to adopt the technology.	(Davis *et al.,* 1989)
Perceived risk	This captures the users' apprehension about the risks involved in using chatbots for banking, reducing their willingness to adopt the technology.	(Kolodinsky *et al.,* 2004)
Self-efficacy	This measures users' confidence in using chatbots for banking transactions, and a higher self-efficacy leads to a greater intent to adopt chatbots.	(Bandura, 1977, 1986, 1997)
Technology Anxiety	This gauges the level of technological anxiety users experience when using chatbots, which negatively impacts their willingness to adopt the technology.	(Bozionelos, 2001)
Personal Innovativeness	This indicates users' willingness to try new technologies, like chatbots, in the banking sector. Greater innovativeness boosts their adoption intent.	
Voluntariness	This refers to how much users feel externally compelled to use chatbots, with lower voluntariness resulting in less willingness to adopt.	(Venkatesh *et al.* 2003; Venkatesh & Davis, 2000; Agarwal & Prasad, 1997; Venkatesh & Morris, 2000)
Digital literacy	This considers the users' familiarity with digital technology, positively influencing their intent to adopt chatbots.	(Ito *et al.,* 2009)

Source: Davis (1989)

factors. Finally, Structural Equation Modeling (SEM) is conducted using Smart PLS version 4.0 to evaluate the relationships between individual-level variables such as demographics, experience, perceived usefulness and ease of use, digital literacy, adoption, and intention.

Table 2 presents the outcomes of the reliability analysis using Cronbach's alpha values. The values are found by applying the ALPHA method in SPSS. The higher Cronbach's Alpha value measures the variables as reliable and consistent. The scale assessing the perceived usefulness of chatbots yields a Cronbach's alpha of 0.919, pointing to excellent internal consistency. This means the items on this scale consistently and reliably measure participants' perceptions about the utility of chatbots. The scale focused on the ease of using chatbots shows good internal consistency with a Cronbach's alpha of 0.879. This indicates that the scale reliably gauges participants' views on how simple it is to use chatbots. For scales measuring facilitating conditions, social influence, security, chatbot design, perceived employment, perceived risk, self-efficacy, anxiety toward technology, quality of information, intention to use, adoption, digital literacy, errors, and challenges, Cronbach's alpha values range from 0.777 to 0.933. These values indicate good to excellent internal consistency, confirming that these scales are reliable and consistent in capturing participants' experiences and opinions regarding chatbot usage. The scale for personal innovativeness shows a Cronbach's alpha value of 0.672, signaling questionable internal consistency. This suggests the items on this scale may not be reliable in measuring participants' innovativeness in relation to chatbot usage.

Table 2. Reliability analysis

Characteristics Studied	Cronbach's alpha value	Reliability of Scale
Perceived usefulness of chatbots	0.919	Excellent
Easiness of using chatbots	0.879	Good
Perceived enjoyment of chatbots	0.844	Good
Perceived risk of chatbots	0.885	Good
Self-efficacy	0.815	Good
Anxiety to technology	0.858	Good
Personal innovativeness	0.672	Questionable
Quality of information obtained from chatbots	0.847	Good
Intention to use chatbots	0.898	Good
Adoption of chatbots	0.803	Good
Digital literacy	0.850	Good
Voluntariness	0.713	Acceptable

Source: Statistically Analysed Data

4. Demographics

The average age of the 195 participants was 27.66 ± 7.70 years. Men made up 54% (n=106) of the study,

and 39% (n=77) were married. Figure 2 presents data on age, gender, income, education, and occupation. For education, 42.6% (n=83) held undergraduate degrees, 56.4% (n=110) had postgraduate degrees, and a negligible 0.1% (n=2) had diplomas. No one had an education level below graduation. Regarding employment, the majority were in the private sector (62.1%, n=121), 28.7% (n=56) were unemployed, 7.2% (n=14) were self-employed, and a scant 2.1% (n=4) were in government jobs.

4.1 Banking Profile of the Respondents

Among the 195 participants, 91 had accounts in private banks, 47 in public banks, and 57 in both types of banks. These proportions equate to 47%, 24%, and 29%, respectively. Figure 3 illustrates the distribution of accounts across various banks. The State Bank of India led the way, followed by HDFC Bank. Regarding the duration of holding a bank account, 36% of participants (n=71) maintained accounts for more than six years. Additionally, 18% (n=36) held accounts for four to six years, 21% (n=41) for less than two years, and 24% (n=47) for two to four years. Notably, a significant 36.4% have been loyal to their banks for over six years. This long-standing relationship implies a level of trust and satisfaction with their banking institution. It also suggests that these customers are more likely to be receptive to new services offered by their bank, including chatbots. While awareness of chatbot services in the banking sector appears high, there's room for improvement. Specifically, 55.9% of respondents indicate a high level of awareness (Figure 4). This finding suggests that banks should amplify efforts to educate their customers about the benefits and availability of chatbot services. Adopting targeted communication and marketing strategies could boost awareness and encourage more customers to engage with these technologies. Regarding actual usage, it's noteworthy that almost half, or 45.6%, of respondents have interacted with their banks' chatbots, indicating a considerable rate of adoption.

When queried about their motivations for using chatbots, a majority—63.1%—highlighted the prompt and accurate responses they receive. This emphasizes the value customers place on speed and efficiency, making it crucial for banks to continue optimizing the accuracy and responsiveness of their chatbot services. The data reveals that a significant 62.6% of users interact with chatbots regularly, suggesting that these services have become an integral part of the banking experience for many. This finding underlines the importance for banks to consistently update and enhance their chatbot offerings to meet the evolving needs and expectations of their customer base.

4.2 Chi-Square Test

Table 3 presents the findings of the Chi-square test, offering valuable insights into individual-level

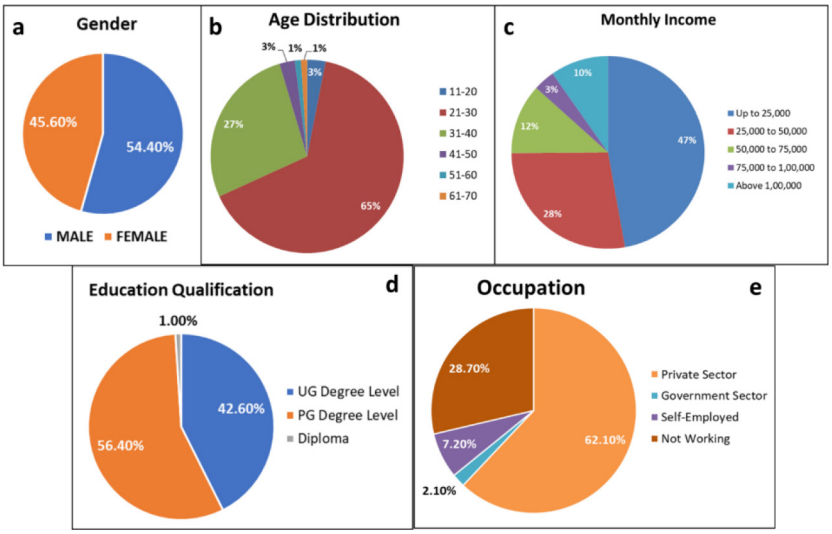


Figure 2. Demographics of the respondents.

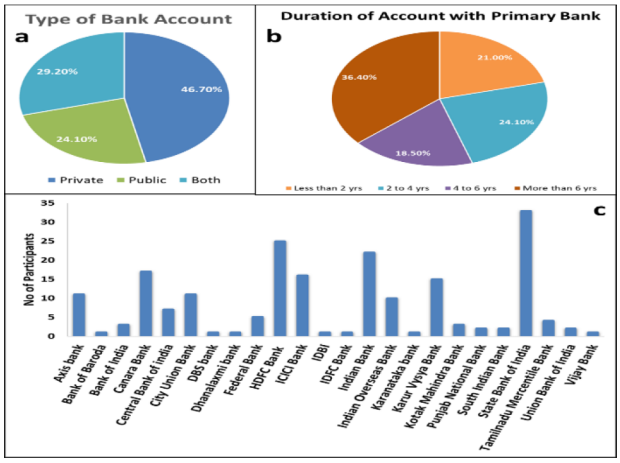


Figure 3. Banking profile of the respondents.

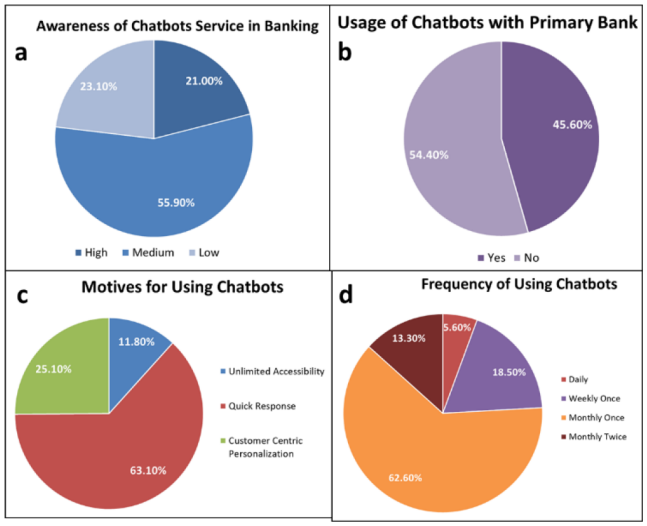


Figure 4. Awareness and motives of using chatbots.

relationships between variables. This helps to illuminate the participants' perceptions and experiences. The study reveals an insignificant relationship between demographic characteristics and selected variables. Specifically, there is no significant relationship between gender and type of bank, age and perceived usefulness, experience and perceived usefulness, average monthly income, and length of holding a bank account, all having a p-value greater than 0.05. This leads to the acceptance of the null hypotheses $H0_1$, $H0_3$, $H0_5$, and $H0_6$.

Similarly, the null hypothesis $H0_2$ is accepted for the types of chatbot usage and comfort level due to the insignificant relationship between the two variables,

Table 3. Relationships between selected variables at individual level

Hypothesis	Variables analyzed	Chi-squared	p-value
$H0_1$	Gender vs. type of bank	0.38	p>0.05
$H0_2$	Types of chatbots vs. comfortability	0.29	p>0.05
$H0_3$	Average monthly income vs. length of holding bank account	0.26	p>0.05
$H0_4$	Perceived usefulness vs. personal innovativeness	0.13	p>0.05
$H0_5$	Age vs. perceived usefulness	0.94	p>0.05
$H0_6$	Experience vs. perceived usefulness	0.11	p>0.05
$H0_7$	Perceived usefulness vs. ease of use	0.000	p<0.001
$H0_8$	Personal innovativeness vs. ease of use	0.000	p<0.001
$H0_9$	Voluntariness vs. ease of use	0.000	p<0.001
$H0_{10}$	Voluntariness vs. Intention	0.000	p<0.001
$H0_{11}$	Intention vs. adoption	0.000	p<0.001
$H0_{12}$	Digital literacy vs. adoption	0.000	p<0.001

supported by a p-value greater than 0.05. On the other hand, perceived usefulness, personal innovativeness, and voluntariness display a significant relationship with ease of use, leading to the acceptance of the alternative hypotheses $H0_7$, $H0_8$, and $H0_9$, which is validated by a p-value of less than 0.0001.

There is a significant relationship between intention and digital literacy with the adoption of chatbot technology by users in the banking system, supported by a p-value of less than 0.0001. In the same vein, voluntariness also has a significant relationship with the intention to use chatbot technology, leading to the acceptance of the alternative hypothesis $H0_{10}$, corroborated by a p-value of less than 0.0001, the study finds an insignificant association between perceived usefulness and personal innovativeness, leading to the acceptance of the null hypothesis $H0_4$, with a p-value greater than 0.05.

Figure 5 depicts histograms and trend distributions among the analyzed variables. Figure 6 provides a visual representation of the SEM model. The Structural Equation Modeling (SEM) technique is a widely utilized approach for examining the interdependencies among variables and for exploring the nature of relationships in a unified framework. In contexts where multiple dependent, independent, mediating, and moderating variables are up for examination, SEM

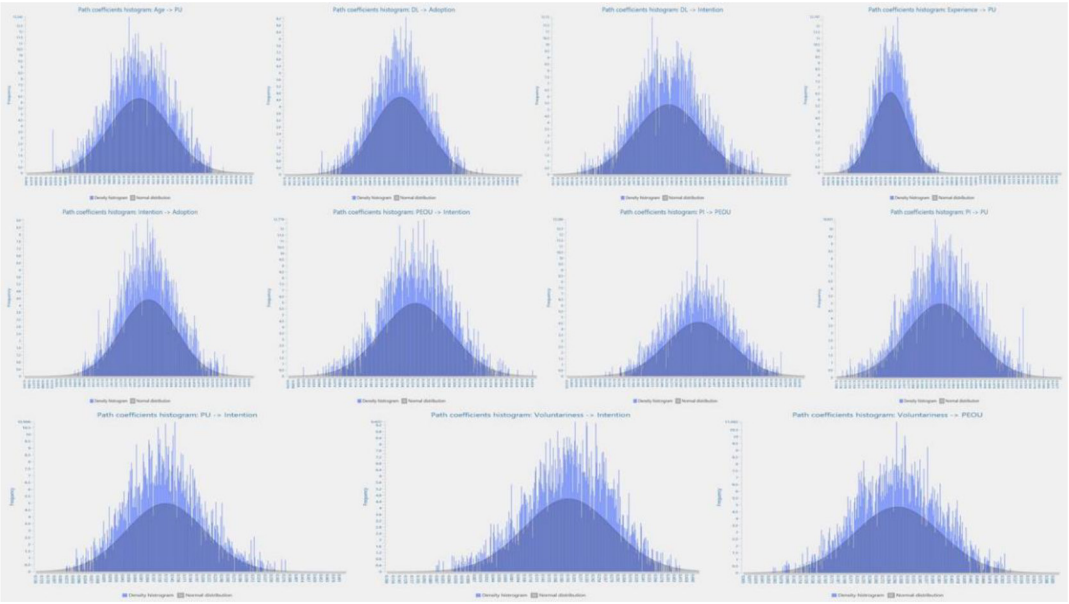


Figure 5. Histograms and trend distributions among the analysed variables.

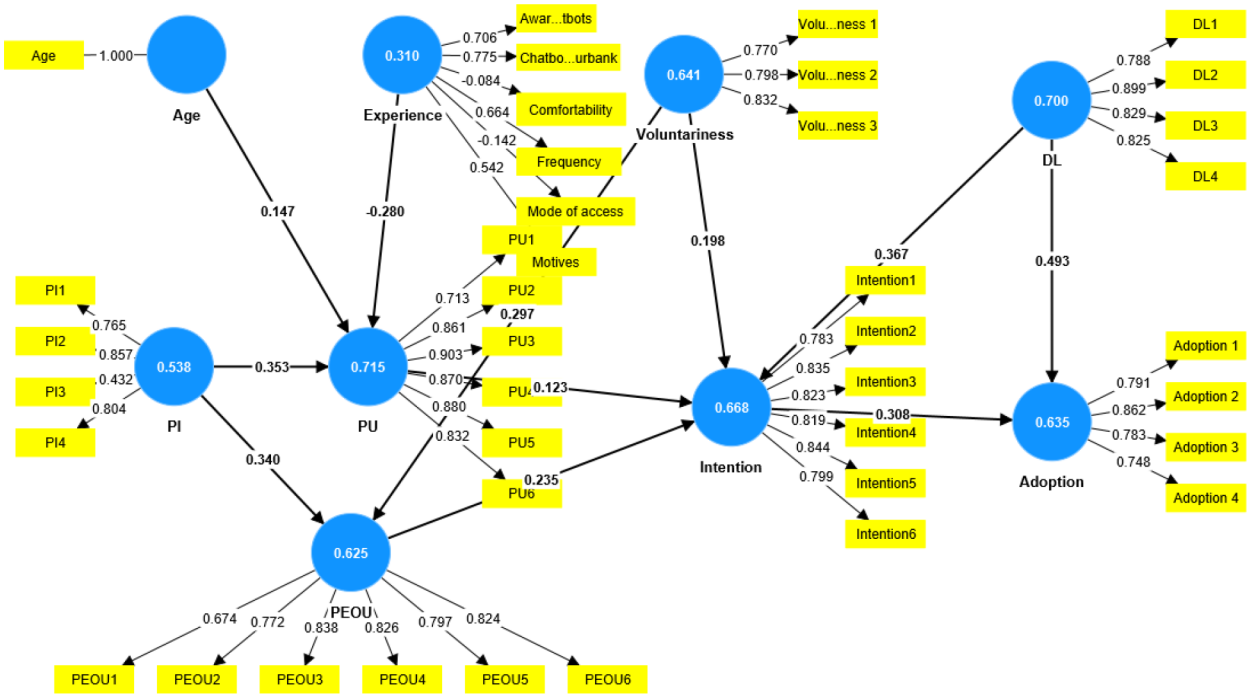


Figure 6. Structural equation model.

serves as an apt analytical tool. It also allows for an overall assessment of the model's fit. The relationships in the SEM are visually represented through path diagrams, where observed variables are displayed in rectangles and unobserved variables are illustrated in ellipses or circles.

Based on the data derived from the SEM analysis, several statistically significant relationships between variables were identified. Notably, there is a significant relationship between age and the perceived usefulness of chatbots, supported by a p-value less than 0.05. A significant positive relationship also exists between

digital literacy and both adoption and intention to adopt chatbots, as evidenced by path coefficients of 0.493 and 0.367 and a p-value less than 0.05. This lends credence to hypotheses 10 and 11 and suggests that individuals with higher levels of digital literacy are more inclined to both intend and adopt chatbots for their banking transactions.

An intriguing finding is the significant negative relationship between experience and perceived usefulness of chatbots, with a path coefficient of -0.28 and a p-value less than 0.05. This might imply that more experienced users tend to be more critical of the utility of chatbots, possibly due to encountering limitations or challenges in their prior interactions.

There is a significant positive relationship between intention and adoption, indicated by a path coefficient of 0.308 and a p-value less than 0.05. This substantiates that users with a stronger intention to adopt chatbots are more likely to do so, thereby affirming the predictive power of intention. In addition, a significant positive correlation exists between the perceived ease of use and the intention to adopt chatbots, with a path coefficient of 0.235 and a p-value less than 0.05. This indicates that users who find chatbots easier to use are also more likely to have the intention to adopt them. Likewise, a significant positive relationship is noted between personal innovativeness and both perceived ease of use and perceived usefulness, evidenced by path coefficients of 0.34 and 0.353 and a p-value less than 0.05. Individuals who score high on personal innovativeness tend to find chatbots easy to use and useful. Finally, a significant positive relationship was observed between voluntariness and intention to adopt chatbots, with a path coefficient of 0.198 and a p-value less than 0.05, indicating that users who feel less externally compelled are more likely to adopt chatbots. These findings elucidate the statistical significance and strength of the relationships among the variables in the SEM model.

5. Discussion

The goal of this study was to explore user experiences and perceptions of chatbots in the banking sector, focusing on the factors that drive adoption. While previous research has delved into the rise of artificial intelligence technologies like chatbots, little has concentrated on the banking industry specifically. Earlier works often prioritised technical specifications over user perspectives. To bridge this gap, our study crafted a detailed conceptual framework, rooted in well-known theories like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). This framework considered variables such as perceived enjoyment, risk, self-efficacy, anxiety, innovativeness, ease of use, usefulness, experience, voluntariness, digital literacy, intention, and adoption (Bandura, 1982; Rogers, 1962; Shoemaker, 1971). Guided by this framework, we tested 12 hypotheses to explore the relationships among these variables in the context of chatbot usage. Data collection involved a questionnaire survey of 195 participants from Coimbatore, Tamil Nadu. The survey assessed participants' demographic data, banking details, and views on chatbot use. Statistical tests, including reliability analysis, chi-square tests, and Structural Equation Modeling (SEM), were employed to analyze the data. The average age of participants was 27.66 years, with a majority being male. Most held postgraduate degrees and worked in the private sector. State Bank of India and HDFC Bank emerged as the most popular banks. Participants reported varying account durations. Reliability analysis showed strong internal consistency in most scales, except for the one assessing chatbot awareness and usage, indicating a need for further refinement.

6. Practical Implications

Investing in chatbot technology demands considerable effort and resources. When implemented effectively, these tools can significantly enhance customer interaction and satisfaction. This research provides valuable insights for banks aiming to develop strategies that enhance user satisfaction with their brand and increase the intent to utilize their services. This is particularly critical in emerging markets such as India, where digital adoption remains comparatively low. The study identifies key elements that can improve satisfaction, thereby increasing the likelihood of attracting more users.

Our findings offer practical recommendations for chatbot designers to incorporate interactive functionalities that foster deeper customer involvement. Previous research underscores the importance of young consumers, as they influence their peers and family members to embrace new technologies (Kaur *et al.*, 2020). This study is essential as it elucidates the factors driving chatbot adoption in the user. The variables examined can guide banks in identifying key aspects to prioritize when shaping customer intent toward chatbot usage. Developers should ensure that chatbots align with the lifestyle preferences of consumers to encourage higher adoption rates. Furthermore, we emphasize that chatbots should deliver information expeditiously, enabling users to save time. They must be intuitive, easy to navigate, and simple to learn. These insights can be particularly beneficial for India's banking sector. As the Indian government continues to promote digital transactions under the Digital India initiative, this study assists financial institutions in understanding the factors contributing to User satisfaction and willingness to adopt chatbot technology.

7. Conclusion

This study offers valuable insights into the factors influencing the adoption of chatbots in the banking sector. It brings to light the critical role played by variables such as age, digital literacy, experience, willingness to use, innovativeness, and intent in shaping user attitudes toward this technology. The findings underscore the need for banks to focus on these key elements when creating user-centric chatbot solutions. By doing so, banks have the opportunity to elevate customer service, streamline operations, and propel digital transformation within the industry. Imminent studies can swell on this research by increasing the sample size for greater reliability and validity. Researchers could extend the study to different geographical locations. Future work could also incorporate more contemporary methods for assessing technology adoption in various economic sectors.

Though the researchers have made efforts to ensure the accuracy of this study, certain limitations remain. First, the sample involved diverse demographics, and the findings were varied. Future research could expand the sample to include participants of specific communities to measure whether the findings remain consistent within that segment. Second, this study focuses on chatbot usage in the banking sector, which is a specific context. Future studies could explore their application in other domains, such as healthcare and various customer service scenarios, including support and recommendation systems. Third, A mixed-method approach could further enrich the understanding of user satisfaction through chatbots. Future studies can also focus on implementing various languages and how privacy and security can be assured to the user can also be explored.

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