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Exploring the Factors Influencing the Adoption and Continuous Engagement in Unlocking the Potential of Technology Driven Chatbots in Banking and Financial Institutions

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Abstract

The integration of chatbot technology in banking and financial sectors has witnessed significant traction, driven primarily by the need to offer efficient customer service and adapt to evolving digital landscapes. This paper investigates deep into understanding critical determinants that drive customers towards adoption of banking chatbots and their sustained usage. Through a comprehensive analysis of data collected from 294 respondents, this study provides insights into the myriad factors shaping customers' behavioral intentions and their decisions to engage with Chatbots continually. To establish theoretical foundation for research, this study leans heavily on two known frameworks - Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Adoption Model (TAM) to identify and assess vital elements affecting consumers' acceptance and utilization of Chatbots within banking and financial services. Chatbot adoption's success hinges on aligning with users' daily routines and lifestyles; a seamless fit increases user engagement and adoption. Such congruence significantly boosts willingness to adopt and engage continuously, suggesting that a keen understanding of end-user's lifestyle patterns is imperative for successful chatbot integration. The value of this paper extends beyond mere academic interest, and holds immense practical value for industry stakeholders, especially those at forefront of digital transformation in banking and financial sectors.

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1. Introduction

Banking and financial institutions are at the crossroads of technological disruption. The young generation prefers online banking to traditional manual banking.[1] Customer service is the foundation of the banking business; hence, a growing number of technologies have been adopted by the banking industry in the last few decades.[2] If the bank pays attention to customer service, it will retain the business in the long run. Technology nowadays helps to improve the customer experience. Chatbot technology, intelligent assistants, and virtual assistant technologies have been widely used for customer service.[3]

The term "chat" is very similar to text-based technology because the first chatbot, "ELIZA," was introduced by Josef and was mainly based on input text matching technology that read text patterns and provided replies to the user.[4] Chatbots are computer programs designed to simulate human conversation that has the ability to communicate in natural language and that can be programmed to interact with human users in a wide range of situations via text or voice interactions.[3,5,6] It can interact with a user in a natural language, such as English, and is often employed for various tasks, including customer service, information retrieval, or

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entertainment. The ecosystem of chatbot technology has voice-based and text-based assistant technology.[5] Chatbots can be operated on various platforms like websites, messaging applications, or phone systems. They can be rule-based, where predefined scripts guide the conversation, or they can employ advanced technologies like artificial intelligence and machine learning to understand user inputs and generate responses.

The government of India has also initiated steps towards encouraging these technologies. The Central Bank of India (Reserve Bank of India) has recently launched DigiSaathi - DigiSaathi, an innovative platform supported by a consortium of Payment System Operators and Participants in India, which encompasses banks and non-banking institutions. This initiative provides 24x7 information on various digital payment products and services. Recognizing the need for cost-effectiveness, convenience, and round-the-clock availability, DigiSaathi employs a chatbot on its website to assist users with their queries. The platform offers multi-language support, allowing users to select their preferred language for a complete and tailored experience. It will assist consumers with their questions regarding digital payments through a website and a chatbot facility. Cost-effectiveness, convenience, and availability make chatbots necessary.

Technology adoption should be viewed as digital transitions that modify positions, not eliminate them. Chatbots help automate monotonous chores so humans may focus on creativity. Chatbots also respond to consumer concerns in real-time, matching their expectation for fast support. Chatbots offer lower fees and 24/7 financial services. However, preliminary studies highlight the need to enhance chatbot usability to facilitate user interaction. It is crucial to address consumer misconceptions regarding chatbot services through improved understanding and open discussions to ensure a successful integration of AI-driven innovation benefiting both the public and financial sectors. As chatbots rapidly expand in the financial industry, there is an urgent need to develop a comprehensive model that explores the key motivations and perceptions driving diverse customer adoption. Chatbot technology is at an emerging level, and factors that influence their adoption are still bleary.

There is very little literature on the adoption of banking chatbots. Few studies have covered the adoption intention and perceived risk of banking chatbots.[7] The theoretical model of UTAUT suggests that the actual use of technology is determined by behavioural intention. The perceived likelihood of adopting the technology depends on the direct effect of four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT (Unified Theory of Acceptance and Use of Technology) and TAM (Technology Adoption Model) are foundational in technology adoption studies. It centers on two main factors, Perceived Usefulness and Perceived Ease of Use, influencing a person's decision to use a technology. Both models shed light on understanding user behaviour toward technology adoption. The unified theory of acceptance and use of technology (UTAUT) model and technology adoption model (TAM) are used in this study to identify the importance of factors that influence technology adoption (Fig. 1). This study will help to identify the factors and their importance that influence the chatbot technology adoption behavior of Indian customers by answering the following research questions aligned with the twin objective of understanding the factors that are leading to the adoption of chatbot technology in the financial industry and how the players in the industry can strategize the effective implementation of the growing technology.

RQ1: What factors contribute to accepting chatbot technology in the banking and financial sector?

RQ2: How can the identified determinants in this study inform the development of effective strategies for implementing chatbot technology in the banking and financial industry?

The study's novelty lies in its empirical investigation of the factors contributing to the increasing popularity of chatbots in the banking industry. While previous research has touched upon the adoption of chatbots, this study delves deeper into customers' specific needs and emphasizes the importance of customization in chatbot solutions. By addressing the unique requirements of clientele, the study highlights the potential for a smoother transition towards using chatbot technology.

The paper consists of seven subsections. The second subsection provides a comprehensive literature review. The third and fourth subsections detail the conceptual framework and methodology, which outlines the fundamental concepts, theories, and relationships. This framework serves as a theoretical lens through which the study explores the factors influencing the adoption of chatbots in the banking industry. The fifth subsection presents the results and findings of the study, followed by a discussion in the sixth subsection. The final subsection concludes the paper and suggests avenues for future research.

2. Literature review

The banking sector has undergone transformative changes in recent decades, driven primarily by technological advancements. Understanding these shifts is paramount for both industry professionals and academic researchers. This literature review delves into three pivotal areas that are shaping the future of banking. Section 2.1 discusses the broad role of technology in the banking sector, offering an overview

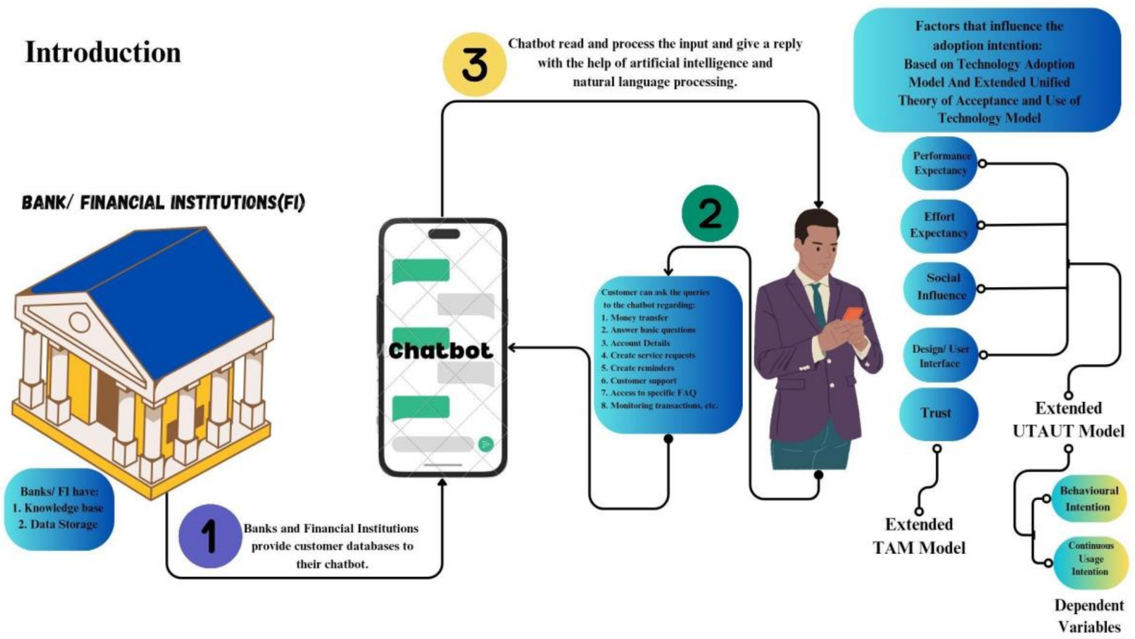

Fig. 1 Analysis of chatbot usage in the banking sector: UTAUT and TAM model.

of its historical and current impact. Section 2.2 zeroes in on the convergence of artificial intelligence (AI) and fintech, two innovation powerhouses redefining banking operations and customer experiences. Lastly, Section 2.3 focuses on chatbots, a manifestation of AI, and their increasing importance in customer service operations. Together, these sections provide a comprehensive exploration of the technological trends and innovations that are steering the banking industry into the future.

2.1 Technology in the Banking Sector

Technology in banking has become the most efficient way to gain customer interaction and build solid relationships with them.[8] Financial technology is becoming the new way beyond e-banking to meet customers' requirements.[9] The increasing number of mobile phone users uptake digital financial transactions.[10] Providers of high-class banking services will get high-class customer retention rates, as well as, they can attract new customers via mouth publicity that will result in high market share and better financial performance.[11] From a competitive perspective, Banking companies provide the core financial services, i.e., landing, deposits, and payments, and are more focused on ultimate customer experience and user-centric services.[12] The implementation of information and communication technology has increased the participation of outsiders; they are general information and communication service providers.[12] Many banking companies have invested funds to develop advanced mobile services to provide the best user experience to their customers.[13] To maintain a dominant position in the financial sector during the fourth industrial revolution, efforts should focus on enhancing core financial services' competitiveness. Technology implementation in banking can lead to accessing financial services and financial inclusion.[14] The financial sector has been one of the most active domains in accumulating ever-increasing amounts of data, accelerating innovation, and developing more successful applications of artificial intelligence (AI) and data science.[15]

2.2 Artificial intelligence and fintech in the banking industry

Consumers are more centric towards AI-based self-service technologies.[16,17] Using the technology, banks, and financial institutions can now avoid duplicity and repetition of work so that human intelligence can focus on other essential and specialized work.[18] To maintain the market share, banks, and financial institutions need to organize targeted internal programs, organizational shifts, and cultural shifts to foster innovation, drive financial technology transformation programs, and invest in financial technology initiatives and enterprises.[19] New options have been given to empower customers by technological advancements in the form of more transparent, cheap prices, removing intermediaries, and easier access to financial information because of technology.[13] How services are provided has undergone profound transformations due to rapid technological advancement.[2] While AI has proven instrumental in streamlining banking operations, elevating customer experiences, and boosting revenue streams, the focus has shifted towards leveraging it for strategic insights. Recent studies delve into AI's potential in streamlining internal audit summaries and assessing strategic endeavors.[8,20]

Nevertheless, embracing AI isn't devoid of hurdles. Issues spanning from its execution to cultural and organizational hindrances have been illuminated in research.[21] The balance between customer privacy and tailored services termed the privacy-personalization paradox, emerges as a prominent concern demanding further exploration.

Furthermore, the COVID-19 crisis introduced its set of complications in AI's adoption within banking. Yet, it is argued that banks must maintain momentum in AI investments, emphasizing their role in bridging digital and physical banking interfaces.[22] Mirroring this, the pandemic has spurred customers towards AI-centric services like chatbots, E-KYC, and robo-advisory platforms.[23]

2.3 Chatbot for Customer Service Operations

Many customer service operations, both high-tech and low-tech, have been redesigned so that technology either complements or replaces the human employee.[24] The increased success of integrating technology into the retail process, which allows for the provision of more individualized services and is supported by a deeper comprehension of the preferences and actions of customers, is the primary factor driving investments in this industry.[25]

The word "chat" (meaning "conversation") with the word "bot" (short for robot) have been combined to form the term "chatbot." Conversational agents, commonly known as chatbots, are another name for chatbots.[26] The rapid changes in retail operations have necessitated the adoption of chatbots as effective and scalable solutions.[27] The increased market share of smartphones and the introduction of text based messaging applications created new opportunities for businesses in the customer service industry.[28] Chatbots rely on sophisticated backend systems to facilitate interactions with end users, enabling a seamless and user-friendly experience and these intelligent backend systems play a crucial role in simplifying engaging with chatbots, making it easier for users to communicate their needs and obtain the desired information or assistance.[29] Chatbots are being increasingly integrated into messaging systems such as Facebook Messenger and WhatsApp, allowing businesses to expand their range of customer care offerings.[30] These companies offered APIs (Application programming interfaces) for chatbot integration so that companies could provide customer services through their channels.[31] This paradigm shift empowers customers to access services, obtain information, and resolve issues on their own terms while also benefiting companies by reducing reliance on human resources and enhancing efficiency.[32] Chatbots save money by replacing personal assistants and boost the user experience with real-time, 24/7 conversations. Chatbots possess the capability to anticipate customer inquiries and provide information proactively. They can also conduct advanced analysis by automatically analyzing conversations to understand customer needs better and improve the quality of products and services.[33] Generally, chatbots are developed to reduce human interaction where the task can be done by technology.[5] Chatbots are regaining popularity due to AI and IoT.[34] It is hoped that chatbot applications and other tech-enabled replacements will increase businesses' sustainability.[35] Because technological progress has occurred at such a breakneck pace in the modern day, it is becoming increasingly important to include the impact of technological development in our deliberations over the optimal way to implement service strategy.[25]

An interactive kind of artificial intelligence known as a chatbot has widespread use in various business sectors, including retail, finance, public administration, and manufacturing.[36] Banking companies use several tools/technologies to serve their customers; a chatbot or virtual assistant is one of the latest disruptions that change how to interact with customers.[37] Customer satisfaction and reliability are the main elements when using banking products.[38] This technical assistance is used to give the customer an enhanced customer service experience.[39] Expectations of customers, knowledge, and usability are some of the primary indicators that will determine whether or not customers are satisfied with bots and whether or not they adopt them[40]). The success of any chatbot only depends on the satisfaction of the customer. Many private and public sector banks introduced chatbots/virtual assistants to communicate and contact customers.[41] Chatbots are known because of personalization and self-learning.[42] Nonetheless, to provide a more customized experience, the chatbot asks users to provide information about themselves.[43] As a result, many new issues regarding users' digital privacy have been raised, and the subject as a whole has become increasingly important.[44]

3. Conceptual framework and hypothesis development

The TAM (Technology Adoption Model) and UTAUT (unified theory of acceptance and use of technology) are well-established and highly regarded models in the field of technology adoption research.[45,46] According to the study, the TAM emphasizes the significance of perceived usefulness and ease of use as the primary determinants influencing the adoption of information technology.[45]

After the TAM model, several theories were introduced with the upgradation and modification of the TAM model.[46] Perceived compatibility and perceived privacy risk are the essential elements of technology adoption.[47] Technology anxiety, perceived trust, and anthropomorphism also affect the adoption of technology in hospitality and tourism.[48] Perceived enjoyment has a positive effect while using technology.[31] Consumer protection has a mediation effect on technology adoption.[49] Information, service, and system quality also affect information technology adoption.[37] Cultural effects also moderate the acceptance of technology.[50] Perceived behavioral intention, attitude, and individual perception also affect information technology adoption.[51] The above-stated constructs are mainly based on TAM and UTAUT (including Extended TAM and Extended UTAUT) models.[46]

This study draws from the TAM and UTAUT models, incorporating variables such as effort expectancy, performance expectancy, social influence, trust, and the design of the chatbot user interface as independent variables. Behavioral intention serves as a mediator between these independent variables and continuous usage intention. Hypothesis development is structured around these identified constructs. To ensure successful adoption of chatbots in banking, it's imperative that these chatbots are user-friendly, delivering prompt and precise responses. Their credibility should be backed by trustworthy sources, and they must offer the highest levels of security and privacy to establish unwavering trust among users.

3.1 Continuous Usage Intention (CUI)

CUI means the possibility of continuously using specific technology soon.[52] According to the study, trust, satisfaction, and perceived usefulness in the banking sector are influential factors that impact customers' intentions to continue using chatbot services.[53] Among these factors, trust was found to have the most significant influence on customers' continuance intentions. Perceived information quality, usefulness, ease of use, and convenience contribute to positive attitudes toward the continuous use of chatbots in banking.[54] The study found that the quality aspects of chatbot services, including understandability, responsiveness, reliability, assurance, and interaction, directly impact users' confirmation and satisfaction levels.[55] These factors, in turn, play a crucial role in influencing users' continued usage of chatbot services.

3.2 Effort Expectancy (EE)

Perceived ease of use is another term for EE that refers to the concept of how easy a system is perceived to be in terms of its functioning.[56] This notion is closely tied to the simplicity of the system's operations and serves as a fundamental aspect of its design.[45] In banking institutions, the effort expectancy factor plays a crucial role in determining the adoption of new technologies.[57] It is believed that the convenience provided by mobile payment services directly influences consumers' behavioral intentions to use them.[58] Based on the above discussion, the following hypotheses can be formulated:

H1(a): Effort expectancy positively affects the behavioral intention to use chatbots for banking/finance.

H1(b): Behavioral intention mediates the relationship between effort expectancy and the intention to use the chatbot continuously.

3.3 Performance Expectancy (PE)

In the UTAUT model, PE is mainly determined by how beneficial something is thought to be. According to the findings of several studies, performance expectations are a significant aspect that plays a role in determining an individual's intention to use technology in banking.[59–61] Additionally, the TAM claims that the perceived ease of use is the primary element that accounts for the variation in perceived usefulness.[45] Usage intention is significantly influenced by perceived utility and enjoyment.[62] The level of performance that a consumer expects is a significant factor that predicts their behavior regarding their intention to adopt technology.[63]

H2(a): Performance expectancy positively affects the behavior intention to use a chatbot for banking and financial institutions.

H2(b): Behavioral intention mediates the relationship between performance expectancy and continuous usage intention.

3.4 Social Influence (SI)

Social influence is defined under the UTAUT model as "the extent to which an individual feels that important others believe he or she should implement the new system."[46] Social influence includes the influence of other individuals on the adoption intention of the technology.[46] Social influence is similar to the subjective norm in the TAM model.[45] In other words, the knowledge and words of encouragement offered by persons close to clients could play an essential part in contributing to the awareness and the intention toward technology on the part of such customers.[64]

H3(a): Social influence positively affects the behavioral intention to use chatbots for banking and financial institutions.

H3(b): Behavioral intention mediates the relationship between social influence and continuous usage intention.

3.5 Trust

Trust is an essential factor influencing the acceptance of self-service technologies.[65] The foundation of trust is the belief that the people in whom one places that trust will not act opportunistically by exploiting the circumstances.[66] A high level of trust leads to a high level of customer loyalty. Consequently, this can develop a healthy customer relationship.[67] Trust is crucial to many economic transactions because humans need to understand their social surroundings or what, when, why, and how people behave.[66] Comprehending the social environment is difficult since people are free agents whose behavior is only sometimes rational or predictable.[66,68]

H4(a): Trust positively affects the behavior intention to use chatbots for banking and financial institutions.

H4(b): Behavioral intention mediates the relationship between trust and continuous usage intention to use chatbot.

3.6 Chatbot design

Design is the chatbot's user interface, abbreviated in the paper as (CD). A design can be classified into two parts, one is functionality and another is security.[53] Studies that have been done in the past confirm that the design favors the behavioral intention to accept technology.[69] This study is trying to suggest that if the chatbot's design is precisely what the customers want, then the adoption rate of the chatbot technology would be higher. Adoption intention will be positively influenced if the design quickly solves their queries or meets their requirements.[37] System designs also indirectly affect users' intent to use the system by virtue of the usefulness and simplicity of its interface.[45,46]

H5(a): Chatbot design/ interface positively affects the behavior intention to use a chatbot for banking/finance.

H5(b): Behavioral intention mediates the relationship between chatbot design/ interface and continuous usage intention.

3.7 Behavioral Intention (BI)

BI shows the probability of an individual's engagement intention towards something new to them.[70] Personality can be explained in terms of behavioral intention.[71] In chatbot adoption, intention can have a positive effect, attracting the individual to try new technological innovations.[71] It has been found that trust has a positive impact on behavior intention. Security threats negatively impact technology adoption, and hence, to encourage adoption, there has to be a good level of trust between the provider and the user.[72]

H6: Behavior intention positively affects the continuous usage intention to use a chatbot.

4. Research methodology

4.1 Research design and measurement scales

This study employs an extension of the UTAUT model with additional constructs related to Chatbot design (user interface) and trust to explore the factors that influence the adoption of chatbots in banking and financial needs.

4.1.1 Research approach

Quantitative Research: A quantitative research approach, utilizing cross-sectional data is used. The approach is deductive, guided by previous research and literature. An objective measurement by generating opinion-based data through surveys is targeted. The purpose of explanatory research is to seek new insights.

4.1.2 Survey method

The primary data collection tool consists of structured questionnaires, some distributed manually and the majority distributed online.

- Survey Instrument: The online survey method was used for data collection. The survey was made available as a Google form with a unique link distributed to prospective banking and financial sector clients. A screening question "Are you about the use of chatbots in banking and financial needs?" was also mentioned. This survey aimed to collect significant insights into the determinants shaping clients' intention to use chatbot services for their banking or financial needs. After sharing the questionnaire with 350 potential banking customers, 56 responses were incomplete. Of these, only 294 complete responses were deemed suitable for analysis in the study. This will help to explore the influence of the variables of the study with firsthand data gathered from the respondents.
- Source of Items: To focus especially on the factors. The items for the constructs are selected based on a review of existing literature. Advanced chatbot technology insights are also incorporated by seeking insights from experts.
- Measurement Scales: Our constructs include Performance Expectancy, Effort Expectancy, Social Influence, Behavioral Intention, Continuous Usage Intention,[46] Trust,[66] and Chatbot Design/User Interface.[73] Consequently, the Details of measurement items are provided in Table 1.

4.2 Sampling and data collection

4.2.1 Sampling technique

A purposive and snowballing sampling technique is used, that involves initiating contact with a relevant small group and leveraging referrals to expand the sample.

4.2.2 Survey structure

The survey comprises two sections. The first section collects data on five demographic characteristics of banking service chatbot users. The second section includes 27 items across seven constructs, rated on a 5-point Likert scale (from "Strongly Disagree" to "Strongly Agree"). These items address latent constructs, and detailed information is provided in Table 1.

4.2.3 Sample size justification

The Sample size selection is based on established guidelines and domain comparisons.

A sample size of at least five times the number of variables is supported.[74] Another method often referred to in the context of PLS-SEM is the "10-times rule" method, as the study outlined.[75] According to this, the sample size should exceed 10 times the maximum number of inner or outer model links pointing to any latent variable in the model. Secondly, the data size typically ranges between 100 and 600 responses in previous studies related to our domain.[9,76–78] There isn't any published data on the exact number of chatbot users, so estimating an accurate number becomes challenging. Therefore, leveraging the above guidelines and aligning with the minimum sample principle necessary for our analysis, we deemed 294 a suitable sample size for our study. This number ensures statistical significance and aligns with established standards in the field. Therefore, leveraging the above guidelines and aligning with the minimum sample principle necessary for our analysis, we deemed 294 a suitable sample size for our study. This number ensures statistical significance and aligns with established standards in the field.

To enhance the comprehensiveness and transparency of our methodology, it's worth noting that the survey design was constructed meticulously to capture all the relevant dimensions of chatbot adoption. The specific questions included in the survey aimed to address the critical factors identified in the literature. However, like any research, potential limitations exist. One limitation might be the reliance on respondents' self-reported data, which might not always capture the depth of their true feelings or experiences. Future studies might consider employing mixed methods or delving deeper into qualitative insights to enrich the findings. PLS-SEM is used to analyze complex inter-relationships between observed and latent variables.

The Technology Adoption Model (TAM) was employed to further delve into the perceived usefulness and perceived ease of use of chatbots, which are foundational constructs of TAM.

Table 1. Constructs and items of the model.

Effort Expectancy [46,79]	EE1	I believe that chatbots are easy to use.
	EE2	I believe that I can use chatbots effortlessly & fluently.
	EE3	I have used a chatbot by myself in the first place.
	EE4	There is no training needed to use a chatbot.
Social Influence[46,79]	SI1	I use chatbot technology because my family or friends are using it.
	SI2	My family and friends, whose opinions I hold in high regard, often use chatbots for their banking needs.
	SI3	My friend suggested that I should use a chatbot for customer service.
Trust[66,80]	TR1	I trust that the chatbot service provider will handle my confidential information responsibly and will not misuse it
	TR2	I am sure about the honesty of the chatbot service provider.
	TR3	I am confident in my relationship with the chatbot service provider.
	TR4	I believe that the information provided by a chatbot is reliable.
Performance Expectancy[46,79]	PE1	I am familiar with chatbots or virtual assistants.
	PE2	The chatbot services are useful for customer service related to banking/finance.
	PE3	Chatbots can address my particular problem/query.
	PE4	I think that chatbot helps to accomplish customer service-related queries quickly.
Behavior Intention[46,79]	BI1	I like chatbot technology.
	BI2	I will use chatbot technology in future, wherever needed.
	BI3	Given a choice, I would choose a chatbot over other forms of customer service.
	BI4	All banking and financial institutions should implement chatbot technology.
Chatbot Design/User Interface[73]	CD1	I feel more engaged When a chatbot starts the conversation with a personalized greeting
	CD2	The chatbot effectively guides me to the specific section of the website where I can find the information I'm seeking.
	CD3	The option to use voice inputs with the chatbot significantly improves my customer service experience.
	CD4	I have received clear communication and guidance from Banking/Financial institutions about how to use their chatbot
	CD5	I value the option to provide feedback or suggestions at the end of a chatbot conversation to express my level of satisfaction or offer recommendations
Continuous Usage Intention[37]	CUI1	Using chatbot services will provide long-term benefits to me.
	CUI2	Whenever I require customer service, I opt for the chat feature.
	CUI3	I am satisfied with the accuracy of the information provided by chatbots when I seek specific details.

Perceived Usefulness determined if users believed chatbots would improve their banking experience. Perceived Ease of Use gauged the respondents' perceptions about whether using chatbots is free from effort.

UTAUT and TAM frameworks were operationalized through a carefully designed questionnaire, where the items for each construct were adapted from previous validated studies, ensuring the reliability and validity of our measures. The responses to these items helped quantify the extent of acceptance and potential adoption of chatbots among the sample. The integration of both UTAUT and TAM in our research offered a comprehensive lens to view chatbot adoption. While UTAUT provided a broader perspective on behavioral intention and the factors influencing it, TAM allowed for a deeper dive into the user's intrinsic motivations and perceptions of the technology. Together, they provided a holistic understanding, enabling us to draw robust conclusions and recommendations for banking and financial institutions looking to optimize their chatbot implementations.

5. Results and findings

In this research, the data analysis was attempted using Smart PLS software version 4.0. The data were analyzed in the following steps: The validity of constructs was checked by examining Cronbach alpha, composite reliability, factor loadings, and average variance extracted (AVE). In the next step, path coefficients were analyzed, and mediation analysis was performed. The analysis of the demographic profile presented in Table 2 was prepared with the help of MS-office software. This study also attempted Importance Performance Matrix Analysis (IPMA).

5.1 Demographic profile of respondents

It should be noted that one-third of the total participants were students, and the other one-third were private and government employees. Almost half of the participants were from urban localities, and the remaining half were from semi-urban, rural, and metropolitan localities. The study examines respondents across diverse ages, qualifications, locations, and professions. Table 2 shows the demographic description of 350 respondents who participated in the survey. The demographic data reveals that chatbot adoption in the banking and financial sector is more prevalent among younger individuals (53.71% falls within the 18-25 years category), males (70.57%), those with higher educational qualifications (majority, i.e., 47.44% are graduates and in urban (54.63%), metropolitan (28.30%) areas. These findings can inform the design and marketing strategies for chatbots in this sector, targeting the demographic groups, that are more likely to engage with these services.

5.2 Analysis of measurement model

Several measurements were employed to comprehensively evaluate the model's reliability, convergent validity, and discriminant validity, including Cronbach's alpha and composite reliability. Table 3 summarizes the factor loadings, composite reliability, Cronbach's alpha, AVE (Average Variance Extracted), and R square, which were instrumental in conducting the assessment.

Table 2. Demographic description.

Variables	Categories	Count	Percentage
Age	18-25 Years	188	53.71%
	26-35 Years	128	36.56%
	36-45 Years	29	8.20%
	46-55 Years	5	1.53%
Gender	Male	247	70.57%
	Female	103	29.43%
Qualification	High school	54	15.44%
	Graduate	166	47.44%
	Postgraduate & above	128	36.58%
	Others	18	0.52%
Occupation	Student		
	Private sector	137	39.14%
	Professionals	84	24.00%
	Government	116	33.14%
	Employment	10	2.86%
	Business	3	.087%
	Other		
Location	Rural	31	8.84%
	Semi-urban	29	8.23%
	Urban	191	54.63%
	Metropolitan	98	28.30%

Based on the data presented in Table 3, Cronbach's Alpha values ranged from 0.739 to 0.892, all surpassing the minimum threshold of 0.7. This indicates strong internal consistency among the measured variables. Additionally, the results revealed that the composite reliability (rho_a) values exceeded the recommended threshold of 0.7, initially established by the study as the minimum acceptable value.[81] The composite reliability values ranged from 0.747 to 0.895, further confirming the robustness and reliability of the data's internal consistency.

To assess the convergent validity, this study examined the comparability of multiple items within a measurement. The average variance extracted (AVE) and factor loadings were evaluated as part of this analysis. The factor loading values between 0.709 and 0.921 fulfilled the threshold requirements, as all the values were higher than the recommended value of 0.7.[75] The AVE values ranged between 0.633 and 0.807, which were higher than the suggested value of 0.5.[75] Therefore, the conditions for convergent validity are all satisfied in this study.

5.3 Analysis of discriminant validity

The Fronell-Larcker criterion is a widely used approach to assess the discriminant validity of measurement models. It involves comparing the square root of the average variance extracted (AVE) by a construct with the correlation between that construct and other constructs.[82] Based on the results

Table 3. Measurement model.

Construct	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted	R Square
Behavioral Intention	BI1	0.848	0.892	0.894	0.755	0.77
	BI2	0.897				
	BI3	0.843				
	BI4	0.888				
Design or Interface	CD1	0.853	0.854	0.856	0.633	
	CD2	0.822				
	CD3	0.811				
	CD4	0.775				
	CD5	0.709				
Continuous Usage intention	CUI1	0.852	0.739	0.747	0.658	0.638
	CUI2	0.825				
	CUI3	0.753				
Effort Expectancy	EE1	0.837	0.818	0.844	0.645	
	EE2	0.864				
	EE3	0.737				
	EE4	0.767				
Performance Expectancy	PE1	0.824	0.891	0.895	0.755	
	PE2	0.849				
	PE3	0.89				
	PE4	0.91				
Social Influence	SI1	0.885	0.881	0.886	0.807	
	SI2	0.901				
	SI3	0.909				

shown in Table 4, it can be concluded that the study has successfully established discriminant validity. The square root of the AVE of all the constructs is found to be greater than the correlation between any two constructs.

5.4 Structural model assessment

As per the previous studies, authors modified the constructs of the original UTAUT model based on their relevance.[83–85] To rate the effectiveness of the suggested model, path coefficients, R Square (Coefficient of determination) and Q square were calculated. Fig. 3 is the replica of the software-generated model reflecting the path coefficients, items loading, p values and R square values. The value of item loadings should be greater than 0.7.[75] The value of R square (0.770 and 0.638) is observed to have significant explanatory power.

In the structural equation modeling (SEM) framework, several constructs influence continuous usage intention mediated through behavioral intention. Specifically, trust and social influence, design user interface, and effort expectancy indirectly impact continuous usage intention via behavioral intention, positioning the latter as a pivotal mediating construct in the model.

In Fig. 2, path coefficients for each construct are detailed. Performance expectancy significantly affects behavioral intention with a path coefficient 0.202 ($p = 0.026$). Effort expectancy exhibits a path coefficient of 0.156, which is statistically significant at $p = 0.012$. While still significant, social influence has a relatively weaker association with behavioral intention, indicated by a path coefficient of 0.106 ($p = 0.04$). Trust emerges as a strong predictor with a path coefficient of 0.266, which is highly significant ($p <0.001$). Design and user interface present the highest path

Table 4. Discriminant validity.

Constructs	Behavioral Intention	Continuous Usage Intention	Design or Interface	Effort-Expectancy	Performance Expectancy	Social Influence	Trust
Behavioral Intention	0.869						
Continuous Usage Intention	0.799	0.811					
Design or Interface	0.788	0.761	0.796				
Effort Expectancy	0.684	0.69	0.593	0.803			
Performance Expectancy	0.798	0.73	0.748	0.718	0.869		
Social Influence	0.622	0.541	0.618	0.402	0.609	0.899	
Trust	0.79	0.735	0.723	0.644	0.775	0.578	0.861

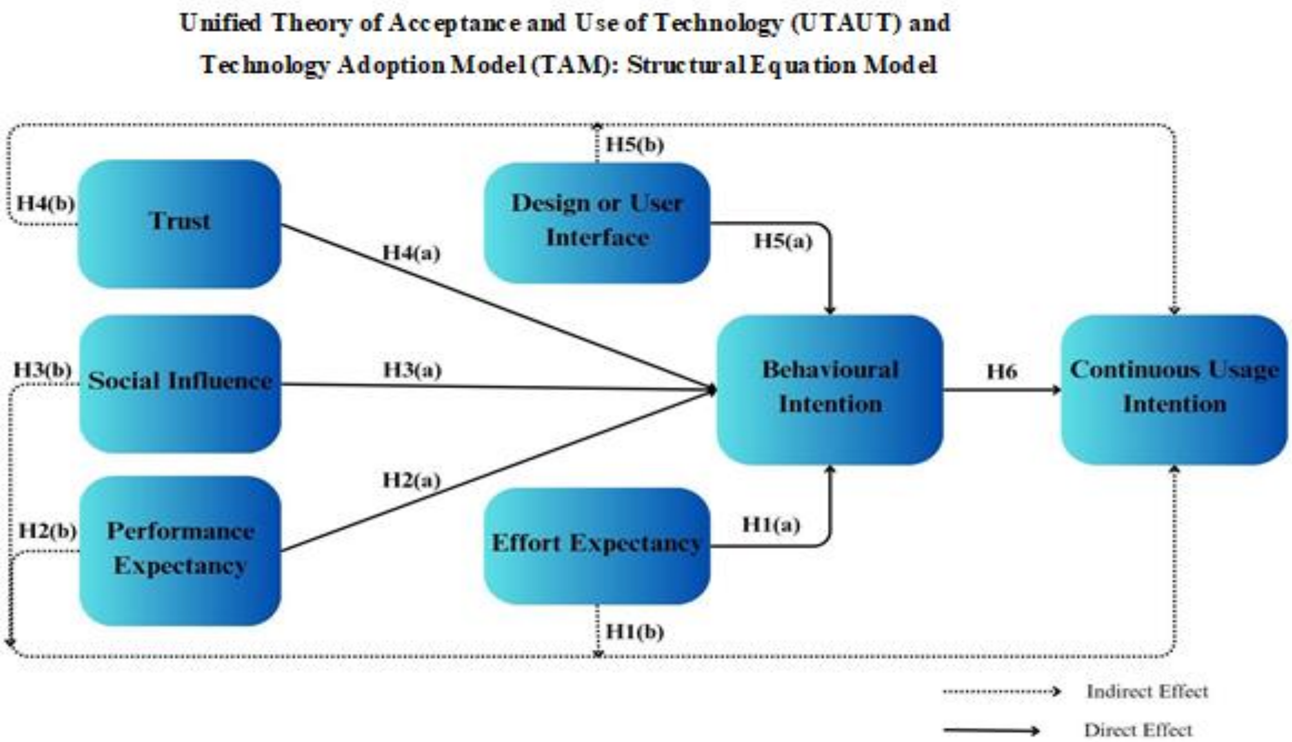

Fig. 2 Conceptual model.

coefficient value of 0.289, which is also highly significant ($p < 0.001$). The summarized results from Fig. 2 are tabulated in Table 5. It's paramount to underscore the considerable and significant mediating effect of the behavioral intention latent construct, as evidenced by its path coefficient of 0.799. Further, the q square values signify the predictive relevance of the model. Table 6 provides the values of q square that were found to be 0.748 and 0.657 for Behavioral intention and continuous usage intention, respectively. These values were found to be greater than 0, signifying the prevalence of the endogenous construct.[86]

5.5 Importance Performance Matrix Analysis (IPMA)

This study uses the Importance-performance map analysis (IPMA) as an advanced approach in PLS-SEM by using the continuous usage intention to use chatbot technology as the target variable. Fig. 4 shows the IPMA results. The importance and performance of all the independent variables (i.e., behavioral intention, design or interface, performance expectancy, effort expectancy, social influence, and trust) were measured.

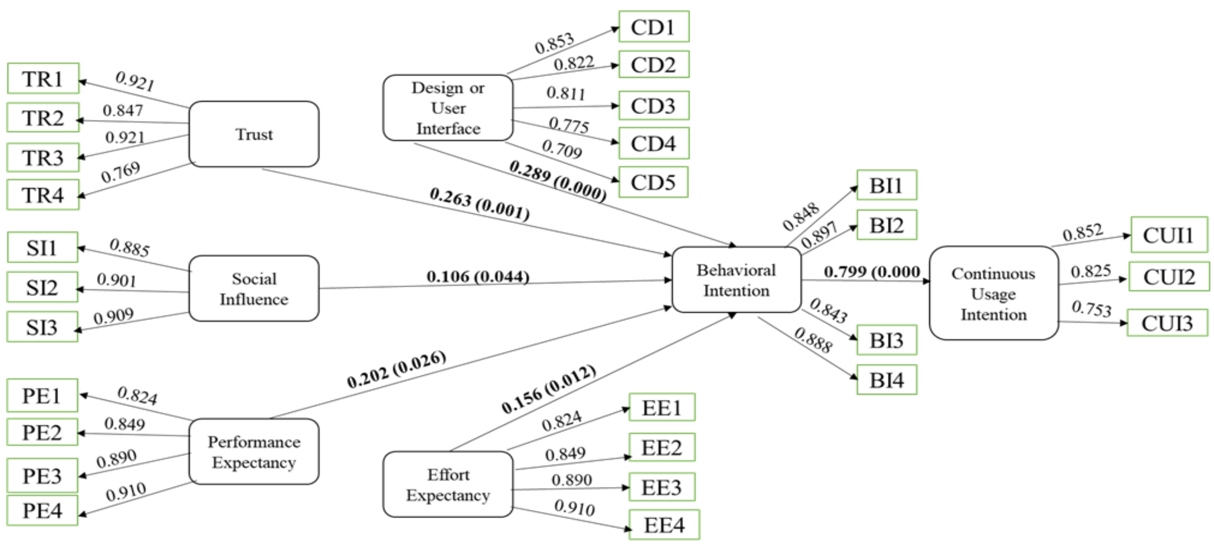

Fig. 3 Strength of the structural model.

Table 5. Values of structural model.

S. No	Hypothesis	Beta	T statistics (|O/STDEV|)
H1(a)	Effort Expectancy -> Behavioral Intention	0.16	2.522*
H1(b)	Effort Expectancy -> Continuous Usage Intention	0.128	2.530*
H2(a)	Performance Expectancy -> Behavioral Intention	0.193	2.227*
H2(b)	Performance Expectancy -> Continuous Usage Intention	0.155	2.207*
H3(a)	Social Influence -> Behavioral Intention	0.106	2.016*
H3(b)	Social Influence -> Continuous Usage Intention	0.084	2.021*
H4(a)	Trust -> Behavioral Intention	0.266	3.230**
H4(b)	Trust -> Continuous Usage Intention	0.213	3.238**
H5(a)	Design or Interface -> Behavioral Intention	0.29	4.213**
H5(b)	Design or Interface -> Continuous Usage Intention	0.232	4.108**
H6	Behavioral Intention -> Continuous Usage Intention	0.799	30.350**

** Significance at 0.05 ** significance at 0.01*

Table 6. Q^2 Criterion values.

Variables	Q^2predict
Continuous Usage Intention	0.657
Behavioral Intention	0.748

Table 7. IPMA performance.

Performance	LV performance
Behavioral Intention	67.506
CUI	73.335
Design or Interface	69.056
Effort Expectancy	76.347
Performance Expectancy	68.566
Social Influence	49.777
Trust	67.24

PLS-SEM is a method for analyzing complex inter-relationships between observed and latent variables. When used in conjunction with PLS-SEM, IPMA extends the findings by visualizing the importance and performance of individual constructs (or latent variables) in the model. The visual representation of IPMA can be easily interpreted by non-technical stakeholders, making it easier to communicate results and strategies. When combined with PLS-SEM, the Importance-Performance Matrix Analysis offers a powerful visual tool that aids in understanding, prioritizing, and strategizing based on the relationships between constructs in a model. This refers to the total effects (both direct and indirect) of a predictor variable on a target construct. In other words, it signifies how crucial a specific construct is in influencing another construct in the structural model.

Importance refers to the total effects (both direct and

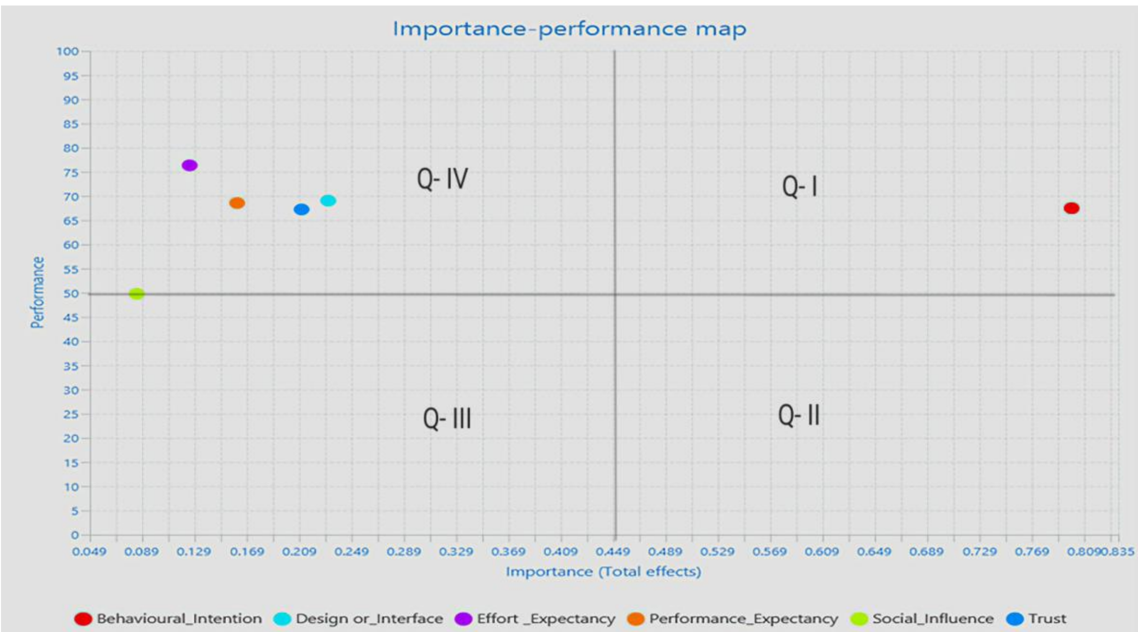

Fig. 4 IPMA.

Table 8. IPMA: total effect.

Total Effect	CUI
Behavioral Intention	0.799
Design or Interface	0.231
Effort Expectancy	0.125
Performance Expectancy	0.161
Social Influence	0.084
Trust	0.21

indirect) of a predictor variable on a target construct. In other words, it signifies how crucial a specific construct influences another construct in the structural model. Performance relates to the average latent variable scores. A higher score indicates that respondents, on average, have more favorable perceptions or evaluations of the respective construct.

The IPMA is divided into four quadrants. Quadrant 1 shows high importance and high performance of behavioral intention (0.799, 67.506). Quadrant 2 signifies high importance and low Performance, and none of the considered constructs fall into this quadrant. Quadrant 3 shows low importance and low performance, while Quadrant 4 represents low Importance and High Performance. Design interface, trust, Effort, and performance expectancy fall in the 4th quadrant. Social influence has a low total effect but moderate performance, lying at the dividing line of quadrants 3 and 4 (see Tables 7 & 8). The positioning of these constructs is indicative of the fact that the technology adoption by the respondents in the Indian Banking sector is yet to mature. This necessitates diving deeper into each quadrant's implication, the status of the banking sector in India, and the implications for stakeholders which has been taken up in the discussion and conclusion section.

LV performance refers to the performance of a Latent Variable (LV). A latent variable is an unobserved variable inferred from measured variables (indicators or manifest variables). Latent variables are the constructs or factors that researchers aim to study, and multiple observed measurements typically represent them. The performance of a latent variable in IPMA refers to the average value of the latent variable scores, which provides insights into how well or poorly a construct is perceived or evaluated by the respondents in a study.

This average score can be understood as the latent variable's " position " along the IPMA chart's performance axis. A higher average latent variable score indicates that, on average, respondents have a more favorable evaluation or perception of the particular construct. Conversely, a lower score would suggest a less favorable perception. In the IPMA, this performance score will determine the vertical position of the construct, with the importance of determining the horizontal position. Constructs can then be grouped into the four quadrants of the IPMA based on their relative importance and performance scores. In summary, "LV performance" in the context of IPMA within PLS-SEM provides a metric to understand how well a particular construct (latent variable) is perceived or evaluated. This aids in the visual representation and strategic decision-making process based on the findings. The vertical position of a construct on the IPMA chart is determined by its LV (Latent Variable) performance score, which represents how favorably respondents perceive it. A higher score indicates a more favorable perception, while a lower score indicates a less favorable one. The horizontal position, on the other hand, is determined by its importance score.

However, the latent performance measure value in Table 7 shows that social influence has the lowest value (49.777), followed by trust, behavioral intention, performance expectancy, design or interface, and effort expectancy respectively. The other factors' LV performance scores are close (in the range 67 to 76). Looking at the importance measure in Table 8, in terms of the total effect, the social influence is observed to be the least impactful factor (= 0.084) in predicting continuance usage intention of using chatbot technology in banking, followed by effort expectancy, performance expectancy, trust, design or interface, and behavioral intention respectively. Social influence has the lowest LV performance score at 49.777, which means that, on average, respondents have the least favorable perception of this construct, as compared to the others. Trust, behavioral intention, performance expectancy, design or interface, and effort expectancy follow in ascending order of their LV performance scores. The remaining factors have relatively close LV performance scores, ranging between 67 and 76, indicating that respondents perceive them similarly and favorably.

To check the collinearity of the structural model, the Variance Inflation Factor (VIF) was examined for every item of the construct (Table 9). VIF is the reciprocal value of tolerance, which should be less than 5.[87] Table 9 shows the outer model values of VIF, and Table 10 shows the inner model VIF values, and all the values are less than 5, showing that, there is no collinearity in the dataset. While all factors play a role in predicting the continued use intention of chatbot technology in banking, it's evident that social influence has the least impact. The close range of performance scores for most factors suggests the parity in their influence. However, for banks aiming to optimize chatbot adoption, emphasizing those constructs with higher performance scores and effect sizes should be prioritized. This insight guides strategic decision-making, ensuring that resources are channeled effectively to enhance user engagement and adoption rates.

Table 9. (VIF): outer model.

Items	VIF	Items	VIF	Items	VIF
CUI1	1.64	CD1	2.296	PE1	1.993
CUI2	1.646	CD2	1.982	PE2	2.195
CUI3	1.305	CD3	2.014	PE3	2.77
BI1	2.497	CD4	1.876	PE4	3.226
BI2	3.198	CD5	1.47	TR1	4.068
BI3	2.07	EE1	1.671	TR2	2.358
BI4	2.682	EE2	2.364	TR3	3.56
SI1	2.394	EE3	1.713	TR4	1.576
SI2	2.363	EE4	1.594		
SI3	2.645				

Table 10. Inner Model (VIF).

Variables	Behavioral Intention
CUI	1
Design or Interface	2.775
Effort Expectancy	2.191
Performance Expectancy	3.843
Social Influence	1.812
Trust	2.98

Table 11 shows the standardized root mean square residual (SRMR) value, which is less than the threshold limit of 0.14,[88] satisfying the goodness of fit criterion.

Table 11. Goodness of fit.

	Saturated model	Estimated model
SRMR	0.075	0.08

6. Discussion

In this study, the constructs used were behavioral intention, design or interface, continuous usage intention, effort expectancy, performance expectancy, social influence, and trust. Our results show that the proposed model is valid. In Fig. 3, the design or interface has the strongest effect on the behavioral intention of customers to use chatbots in online banking services.[38,73] On the other hand, social influence is the least impactful factor on customers' behavioral intention towards adopting chatbot technology in banking.[89,90] This study's findings have several critical managerial repercussions for the banking industry.

Trust also influenced customers' plans to use chatbots in the banking industry. The results show that customers are more likely to use chatbot technology if they think it is secure.[91] In addition, an Importance-performance map analysis (IPMA) was carried out as part of this research (Fig. 4). This more advanced PLS-SEM method uses the continuous usage intention of chatbot technology as the target variable. It is shown that social influence is considered the least impactful factor for forecasting continuing usage intention of employing chatbot technology in banking (Tables 7 and 8). This is true even though the importance and performance measures were considered. Therefore, financial institutions should emphasize socially influencing customers to achieve maximal utilization of chatbot technology to resolve customers' difficulties.

The adoption of chatbot services in the banking sector has proven to be highly beneficial, improving customer service and reducing costs.[47] It is crucial for the financial services industry to understand the factors that influence customers' acceptance of this technology. This study examined various constructs such as behavioral intention, design or interface, continuous usage intention, effort expectancy, performance expectancy, social influence, and trust to assess their impact on customers' willingness to adopt chatbot technology.[47]

Our findings indicate that the proposed model is valid, and we identified several key factors that influence customers' behavioral intention to use chatbots in online banking services. Among these factors, design or interface emerged as the most vital determinant, suggesting that chatbot interfaces' user-friendly and visually appealing design encourages customers to embrace this technology. On the other hand, social influence was found to have the least impact on customers' behavioral intention to continue using chatbot technology in banking, even when considering both importance and performance measures (Tables 7 and 8). This suggests that financial institutions should focus on other influential factors rather than social influence to maximize the utilization of chatbot technology for resolving customer difficulties. In the SEM framework using the UTAUT and TAM model, behavioral intention is a pivotal mediator affecting continuous usage intention. While performance expectancy, effort expectancy, and trust significantly influence behavioral intention, the design user interface emerges as paramount in its impact on behavioral intention (path coefficient = 0.289, $p < 0.001$). It can be inferred that the design and user interface play a significant role in influencing continuous usage intention, mediated through behavioral intention, underscoring its importance in user engagement and retention strategies.

The presence of behavioral intention in the Ist quadrant of IPMA suggests that users are strongly inclined to adopt the technology, and their current perceptions are positive. However, intention alone doesn't guarantee actual adoption. For technology to be embraced fully, other constructs, especially those in Quadrant 4, need attention. The constructs in the 4th quadrant, such as design interface, trust, effort, and performance expectancy, have favorable perceptions but are not deemed as essential by respondents. This could imply that while the technology might be user-friendly and trustworthy, other external factors might be inhibiting its full adoption. The positioning of the Social Influence, straddling quadrants 3 and 4, is intriguing. While it has moderate performance, its influence on adoption isn't strong. This suggests that external opinions and societal perspectives might not be the dominant forces in technology adoption in the Indian banking sector, as they might be in other cultures or sectors. The IPMA suggests that while many factors have favorable perceptions, with scores ranging between 67 and 76, social influence stands out as an area of concern, having the lowest performance score of 49.777. The constructs of trust, behavioral intention, performance expectancy, design or interface, and effort expectancy, although higher than social influence, also have varying levels of perception, suggesting that there might be room for improvement in these areas. Overall, the findings emphasize the need to closely evaluate and potentially address the areas of social influence, trust, and other factors that scored lower on the LV performance scale to enhance the overall effectiveness or success of the underlying model or intervention being studied.

Our study highlights the importance of design or interface, trust, and other relevant factors in driving customers' intention to use chatbots in the banking sector. These findings have significant managerial implications for financial institutions aiming to enhance customer experience and effectively implement chatbot technology. The research highlights that users' willingness to adopt chatbot technology in the banking and financial sector is significantly influenced by how well they perceive chatbots to align with their lifestyles. This study offers theoretical and practical contributions, augmenting the empirical knowledge on consumer perceptions of chatbot utilization in financial services.

7. Conclusion and Future Scope of the study

Design and User Interface is crucial for continuous usage intention. Enhancing user interfaces can boost engagement and retention. A positive inclination towards technology doesn't guarantee actual adoption. Intention and action need alignment. Quadrant 4 Constructs in Fig. 4, show that despite positive perceptions, certain constructs like trust, effort, and performance expectancy need more focus to drive adoption. Social Influence holds limited sway in the Indian banking sector. Relying solely on peer endorsements may not be effective. Continuous Feedback is essential for refining user experience and ensuring sustained technology adoption. Hence a multifaceted strategy addressing design, trust, barriers and consistent feedback is essential for optimal technology adoption in the Indian banking sector.

Recent advancements show that the banking sector is witnessing an exciting transformation, especially with the integration of chatbots. This study has meticulously examined the pivotal elements influencing the surge in chatbot adoption. As autonomous digital intermediaries, chatbots have heralded a new era in customer service by delivering instant solutions and real-time feedback, thus amplifying the banks' proficiency in addressing client queries. To achieve more widespread acceptance of chatbot technology, banks must align their chatbot strategies with the distinctive expectations of their clientele. Personalizing the chatbot experience ensures a seamless induction of customers into this innovative ecosystem.

Moreover, banks are responsible for enlightening their customer base about the pragmatic advantages of chatbots. By underscoring chatbot interactions' expedient and practical facets, banks can dispel any lingering hesitancy and foster a more accepting attitude towards this technological shift. Setting up a dedicated channel for feedback on chatbot interactions is also beneficial. Such a mechanism affirms the bank's commitment to quality and pinpoints areas for enhancement. Continuous feedback ensures the evolution of chatbot interfaces in harmony with the dynamic expectations of users. This study paves the way for financial institutions, delineating a path to refine their offerings with technological adeptness. By capitalizing on the chatbot revolution, banks are poised to redefine customer engagement, streamline operations, and enrich the banking experience for their users.

It's paramount to acknowledge the vast potential for future exploration. Areas such as chatbot emotional intelligence, multilingual capabilities, or integration with other fintech solutions could be potential avenues for subsequent research. As the chatbot technology domain continually expands, future studies can delve deeper, harnessing uncharted territories and bringing forth a more comprehensive understanding of the subject. By shedding light on genuine consumer perceptions and expectations, the study offers a roadmap for enhancing chatbot design, functionality, and user experience to increase adoption rates and sustained interactions. This research contributes significantly to the empirical knowledge pool, setting the stage for further explorations and developments in chatbot utilization in financial services.

Implications

The Indian banking sector, historically rooted in traditional practices, has been experiencing digital transformation. While urban areas have seen a surge in technology adoption, rural areas, which constitute a significant portion of the customer base, remain a challenge due to factors like digital literacy, infrastructure, and inherent resistance to change. The positioning of the constructs indicates a disparity between the potential of the technology and its actual adoption. For banks, this signals an opportunity to bridge the gap. They need to amplify their efforts in areas beyond just improving the design interface or ensuring trust. Tailored training programs, awareness campaigns, and more accessible customer support can be instrumental. With the evidence pointing towards an immature technology adoption phase, policymakers need to develop and implement strategies promoting digital literacy, especially in underserved regions. Tech Developers: There's room for innovation in creating more localized and accessible solutions, catering to the unique needs and challenges of the Indian population. While there's evident interest and positivity toward technology adoption in the Indian banking sector, a holistic approach, addressing both technological and sociocultural factors, is essential for maturity.

Limitations

The present study, though insightful, comes with certain constraints. The participant pool/sample was limited, encompassing 294 respondents, predominantly younger and highly educated with proficient financial and digital skills. As a result, the insights gained might resonate more with a scholarly demographic than the broader banking clientele. Future studies should encompass a more diverse audience and a larger sample for more encompassing insights. Furthermore, this research didn't hone in on chatbots from particular banks, presenting an opportunity for subsequent studies to delve into specific banking chatbot systems. Investigating speech-driven technology and probing into privacy issues also presents promising avenues for future exploration.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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