

Is banking chatbot adoption reshaping banking services? An Indian perspective

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Abstract

Artificial Intelligence is emerging as a new normal in the technological world. The banking sector is not exempted from this scenario. There are bushels of studies available on chatbots in various sectors. However, few studies discussed the banking chatbot adoption intention, especially in India. This study dealt with banking chatbot adoption in India using the extended UTAUT model with the variables like effort expectancy, performance expectancy, perceived trust, anthropomorphism, and perceived enjoyment, which affect the banking chatbot adoption intention in India. A preliminary survey is carried out with the help of a structured questionnaire, and the structural equation modelling (PLS-SEM) Partial Least Square approach is used to validate the suggested model. The proposed findings given in this study will help the customers be aware of more services available in banking chatbots and provide vital insight for bankers in enhancing the chatbots services, which may reduce the workload for the bankers.

Keywords— Artificial *Intelligence, Anthropomorphism, Banking chatbots, PLS-SEM, UTAUT.*

Introduction

Artificial Intelligence (A.I.) is thriving in the technological world. The great majority of such technological developments have been supported by the vigorous growth of machine learning and artificial intelligence (AI) technology. AI grows more intelligent and useful for various applications as more data is fed into it. In 2022, AI-based products experienced unprecedented growth thanks to chatbots, automated vehicles, and cyber security, to mention a few. The generation of nearly human-like speech and activities by Artificial Intelligence computers was made possible by highly effective language framework. As they swept through industries including banking, education, government, health care and so on to mention a few, chatbots stepped out and firmly established themselves.

The banking chatbots leverage artificial intelligence to interpret and address the inquiries of users effectively. They utilize natural language processing, accessing the databases for data retrieval for

executing the tasks. The banking chatbot enables the financial institutions to deliver personalized automated service. This is done by meeting customer needs comprehensively, optimizing the bank's efficiency and resources simultaneously. The impact of A.I is highly seen in the banking sector. Banking has faced numerous changes since the advent of the internet industry. Mainly after mobile banking, a lot of vital services were delivered through mobile apps. Among the services, payment is considered a significantly impacted service due to the many third-party aggregators. In this scenario, banking chatbots are also getting popular among tech-savvy users.

In the case of banking, chatbots combine technology with the touch of humans to provide optimum and seamless services. In the banking sector, chatbots help customers acquire various services like account opening, balance checking, notification and reminders, financial advice assistance, monitoring of accounts, processing of payments, and preventing fraudulent activities. In the case of bankers, it helps acquire new customers, reduce query workload, and get feedback from customers. Chatbots provide optimum customer service with a personalised customer experience by automating the banking query section compared with traditional payment methods. Chatbots are inexpensive. According to Accenture analysis, fifty seven percentages of businesses believe chatbots may generate significant investment returns with less effort. With 79 percent of interactions being effective, chatbot implementation in mobile banking applications will be the most popular channel for chatbot-driven client communications in 2023. This supremacy is caused by a number of factors, chief among them a growth in consumer demand for application-based banking and the successful pioneering development of banking chatbots like Erica from Bank of America. It resulted in increased productivity of the agents of banks and decreased customer support costs. The working of chatbots is quite complicated but understandable. According to the author (Adamopoulou 2020), chatbots consist of five components. They are the user interface, user message analysis component, dialogue manager, data sources and response generator. The user interface gets the user's input query, and user message analysis scrutinises the input query and filters out the associated entities. After that dialogue manager helps in-keep and updating the conversation context for deciding to take action on the input query, the data sources consist of enormous data that can exist in the database or knowledge base. Using API calls, the database can be accessed. And finally, the response generator makes the responses in the actual language, which are delivered to the user. According to the Humley survey (Waterman 2018), 2/3 of the respondents felt that chatbots powered by A.I. would be helpful to assist, and nearly half percent would communicate with chatbots instead of a real human to clarify their questions. As per Business Insider, chatbots will save up to \$11 billion annually by 2023 in the banking, retail and healthcare sectors. Furthermore, the Capgemini report found that 70 percent of consumers will use voice assistance rather than visit banks or shops in the next three years. Major public and private sector banks have their AI-powered chatbots. E.g. SBI Intelligence Assistance (SIA) acts as a bank representative and helps in everyday banking tasks. Moreover, iPal from the ICICI bank clears queries through Google Assistant and Amazon Alexa. YES ROBOT of YES Bank helps with multiple tasks like applying for a loan, managing credit cards, checking balances, and making a transaction. Likewise, HDFC bank also automates its service through Electronic Virtual Assistance (EVA). In 2020, by partnering with AI-based SaaS voice automation platform Vernacular A.I, Axis bank provided the voice automated A.I. solution to their customers. There are various studies available on chatbots in public transportation (Kuberkar 2020), brand love (Trivedi 2019), the overall financial industry (Jang 2021) (Sugumar 2021) (Hwang 2021), Smartphone chatbots (Kasilingam 2020) and enterprise context (Brachten 2021) and only a few studies are dealt with banking chatbots (Pal 2019) (Suhel 2020) (Nguyen 2021) (Mogaji 2021). The Unified Theory of Acceptance and Use of Technology (UTAUT), which was developed by Venkatesh et al. (2003), is extended in this study. By using the UTAUT model in a current research environment, this study will expand its scope. Our results will help financial service providers in developing markets to suggest and carry out initiatives that will raise the calibre

of their chatbot services and products, thereby improving client experiences and interactions. Along with the UTAUT variables like performance expectancy and effort expectancy, perceived trust, perceived enjoyment and anthropomorphism were introduced. This research will assist the banks in improvising their chatbot service by adding a needed update to provide optimum customer service.

Theoretical Background and Research Hypotheses

In this study, the UTAUT model is used. Because it contains a variety of acceptance models and uses cutting-edge information technology validated by testing in previous studies, furthermore, this model is considered a combination of various UTAUT variables like effort expectancy, performance expectancy and extended variables like anthropomorphism, perceived enjoyment, and perceived trust.

Performance Expectancy

Performance expectancy is defined as the extent to which an information system or technology enables customers to accomplish specified tasks (Alalwan & Dwivedi 2017) (Baabdullah 2019) (V. Venkatesh 2012). Previously, performance expectancy had a significant influence on consumers' trust and desire to accept technology (V. Venkatesh 2012). Previous studies on chatbots (Balakrishnan 2022) (Mogaji 2021) (Sugumar 2021) (Kuberkar 2020), mobile technology (Jambulingam 2013), mobile payment (Slade & Michael 2014) (Alalwan & Dwivedi 2017) (Baabdullah 2019) (Sarfaraz 2017), e-banking (Ghalandari 2012) found that performance expectancy has the strongest influence on adoption intention of banking chatbot. Thus we hypothesise that.

H1: Performance expectancy had a significant impact on banking customers to adopt banking chatbots

Effort Expectancy

Effort expectancy is the level of an individual understanding of users' ease in using technology (V. Venkatesh 2012). If the system reduces the work or effort of banking activities, the customers will prefer the banking chatbot for their banking-related needs and queries. The past studies on chatbot (Balakrishnan 2022) (Mogaji 2021) technology adoption (Wilson-Evered 2012) (Alshare 2014) and mobile payment (Alalwan & Dwivedi 2017) also found that effort expectancy had a significant impact on behavioural intention to adopt mobile banking. Hence the following hypothesis is proposed.

H2: Effort expectancy had a significant impact on banking customers to adopt banking chatbots

Perceived Enjoyment

Perceived enjoyment is defined as the extent to which activities involving a particular system are recognised as joyful in and of themselves, independent of any performance outcomes ensuing from the use of the systems (Chao 2019). In addition, the perceived enjoyment of a person leveraging technology influences their intention and intensity of use (Venkatesh 2008). There are many studies with different contexts like Enterprise (Brachten 2021), Mobile games, internet activities, mobile payment (Handarkho 2019) and online payment (K. Rouibah 2016), and most significantly influences the adoption intention. In some cases, hedonic motivation also has similar characteristics to dealing with pleasure and happiness (Venkatesh 2012), significantly affecting the banking chatbot adoption intention. So if a customer likes the banking chatbot experience, they will intend to use this service continuously for banking. Hence the hypothesis was suggested.

H3: Perceived enjoyment had a significant impact on banking customers to adopt banking chatbots

Perceived Trust

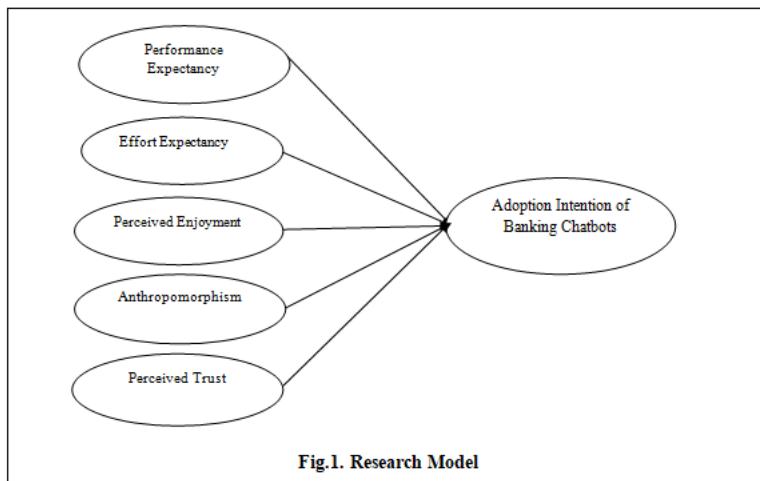
(Venkatesh & Thong 2011) asserted that the happiness of the customers, together with trust, were the two crucial predictors of continuation and adoption intention in electronic commerce research. In a wider context, trust can be defined as an individual's belief that other individuals will behave and do acts within an expected level. If there is more risk in the services, it will result in the loss of trust. Previous research has also shown that trust motivates both behavioural and adoption intentions in a variety of circumstances, including chatbots (Eren 2021) (Nguyen 2021), online purchases (Bao et al. 2016) and mobile payments (Singh & Neena 2020) (Liébana-Cabanillas 2018). Most of the studies resulted in significant results on these online services. As per the previous studies, we hypothesise that.

H4: Perceived Trust had a significant impact on banking customers to adopt banking chatbots

Anthropomorphism

Anthropomorphism is the fundamental desire of humans when communicating with machines (Wagner 2019). Anthropomorphism in the area of chatbots is explained as the degree to which consumers perceive human characteristics in an artificial machine by giving such non-human characters with human traits, intentions, emotions and behaviours (Epley 2007). The anthropomorphism function makes these social robots appear more authentic, potentially increasing human-robot interactions (Sheehan 2020) (De Graaf 2013). If the system provides human-like service fruitfully, the customers will prefer chatbots rather than human service. Moreover, based on previous studies, anthropomorphism positively influences the adoption intention of banking Chatbot (Kuberkar 2020) (Araujo 2018) and attitude (Balakrishnan 2022). Moreover, some studies give insignificant results on banking chatbot adoption (Balakrishnan 2022) (Sugumar 2021). However, as per the various studies, we hypothesise that

H5: Anthropomorphism significantly influences the adoption intention of banking chatbots among banking customers.



Methodology

The study was undertaken online using Google forms to collect efficient and valuable data. Our study model is made up of six constructs. Due to a lack of relevant data about the population, the convenience sampling method was employed for sample collecting, a broader phase that incorporates a range of procedures for selecting respondents. There are separate studies available for different

digital banking platforms. But studies on banking chatbots are fewer in India. And extended the UTAUT framework with new variables added those are relevant to the scope. The respondents were active banking customers using banking chatbots through their smartphones, and 198 respondents were picked at random from four zones of Tamil Nadu state in India. The questionnaire is segregated into two portions. The initial part of the questions aimed at the respondents' characteristics. In the next section, twenty- four questions on the five categories of the UTAUT extension model were asked on a five-point Likert scale. The theoretical basis was gathered through secondary sources such as journals, periodicals, and research papers, accessed using databases such as Google Scholar, EBSCO and Science Direct.

Analysis of Data and Results

The Smart PLS 3.0 is utilised for model estimation for its component-based approach, which emphasises sample size and residual distribution. Initially, the model of measurement was tested to check validity and reliability. After that, the structural model will be estimated to test the hypotheses. The tables of standardised item loading, composite reliability (C.R.), p-value, t-value, and Average Variance Extracted (AVE) of every variable were listed below. We notice that all constructs are higher than the specified criterion, indicating that our scale has stronger reliability and convergent validity.

Table 1 Characteristic of Respondents

Characteristics	Values	Frequency	Percentage (%)
Gender	Male	141	71
	Female	57	29
Age	Below 30	92	47
	31-40	44	22
	41-50	32	16
	Above 50	30	15
Residence	Rural	12	6
	Semi-urban	80	40
	Urban	106	54
Educational qualification	School education	15	7
	Graduate	132	67
	Post Graduate & Above	51	26
Mode of chatbot usage	Through text	106	54
	Through Voice	42	21
	Both text and voice	50	25
Name of the Chatbot using	SIA (SBI)	21	10
	CANDI (Canara bank)	23	12
	iPal (ICICI)	62	31
	Yes Robot (Yes bank)	22	11
	EVA (HDFC)	51	26
	Others	19	10

Source: Primary Data calculated by utilising SPSS 16.0

Collectively 217 responses were gathered from the customers, and only 198 were valid. Table 1 represents the demographic characteristics of the participants. Male respondents comprise 71 percent ($f=141$), while female respondents account for 29 percent ($f=57$) of those who responded to the survey. Moreover, two influential groups that dominated the surveys were Below 30 and 31-40, which occupy

47 percent and 22 percent. In the case of educational qualification, the major respondents were graduates (67%) and followed by Postgraduates and above (26%). Additionally, most of the respondents were living in urban areas (54%), and another significant population was living in semi-urban (40%). In the case of usage of chatbots, most respondents prefer to use through text mode (54%), and another significant set of the population prefers to use both text and voice in tandem. Furthermore, iPal (ICICI bank) and EVA (HDFC bank) dominate chatbot usage with 31% and 26%, respectively.

Table 2 Results of the Measurement Model

	Items	Loadings	Cronbach's Alpha	CR	AVE
Adoption Intention	AI1	0.723	0.824	0.884	0.656
	AI2	0.834			
	AI3	0.860			
	AI4	0.817			
Perceived Enjoyment	PEJ1	0.839	0.899	0.929	0.766
	PEJ2	0.890			
	PEJ3	0.892			
	PEJ4	0.892			
Effort Expectancy	EE1	0.773	0.802	0.871	0.628
	EE 2	0.775			
	EE 3	0.794			
	EE 4	0.826			
Anthropomorphism	ANT1	0.673	0.747	0.837	0.564
	ANT2	0.763			
	ANT3	0.708			
	ANT4	0.849			
Perceived Trust	PT1	0.822	0.846	0.896	0.684
	PT2	0.874			
	PT3	0.785			
	PT4	0.824			
Performance Expectancy	PE1	0.769	0.817	0.879	0.646
	PE2	0.772			
	PE3	0.806			
	PE4	0.865			

Source: Primary Data calculated by utilising SmartPLS 3

Model for Measurement assessment

In order to make sure that the measurements are precise and represent the acknowledged conceptual elements, the model for measurement must be evaluated. As per Table 2, the values of Cronbach's alpha varied from 0.747 to 0.899, showing that they were all above the 0.7 criteria. The results also revealed that the values of composite reliability (C.R.) ranged from 0.837 to 0.929, above the acceptance criterion of 0.7. The values of AVE extended from 0.564 to 0.684, showing that they were all higher when compared to the permissible value of 0.5. (Hair et al. 2014) The factor loadings values fulfilled the criterion, as shown in Table 2, with most of them above the required threshold of 0.7.

Assessment of structural model

The structural evaluation framework helps to test hypotheses, as shown in Table 3 and Figure 2. As per this study, effort expectancy significantly influences the adoption intention of banking Chatbot. As an outcome, H2 ($t = 5.098, p = 0.000$) is accepted. Moreover, the findings showed that perceived enjoyment and performance expectancy was also impacting the adoption intention of banking Chatbot, respectively. As an outcome, H5 ($t = 3.104, p = 0.002$) and H1 ($t = 1.983, p = 0.048$) were accepted. Furthermore, the results show that perceived trust and anthropomorphism had a less significant impact on the adoption intention of banking chatbots. Hence, H3 ($t = 1.943, p = 0.053$) and H4 ($t = 1.408, p = 0.160$) is not supported.

Table 3 Hypotheses Testing Function

H	Association	SD	t-value	p-value	Findings
H-1	PEJ → AI	0.019	1.983	0.048	S
H-2	EE → AI	0.118	5.098	0.000	S
H-3	ANT → AI	0.018	1.943	0.053	NS
H-4	PT → AI	0.021	1.408	0.160	NS
H-5	PE → AI	0.121	3.104	0.002	S

Source: Primary Data calculated by utilising SmartPLS 3

*H-Hypotheses, AI- Adoption Intention, PEJ- Perceived Enjoyment, EE- Effort Expectancy, ANT- Anthropomorphism, PE- Performance Expectancy, PT- Perceived Trust, S-Supported, NS-Not Supported

The "Heterotrait-Monotrait ratio (HTMT)" metrics for measuring discriminant validity were studied in this work, as suggested by (Hair Jr 2017) and relied on prior assertions. Because the results were mostly less than the required threshold of 0.9 value, the HTMT criteria were satisfied, as shown in Table 4.

Table 4 Ratio of Heterotrait- Monotrait (HTMT)

	AI	PEJ	EE	ANT	PT	PE
AI						
PEJ	0.810					
EE	0.313	0.875				
ANT	0.989	0.313	0.792			
PT	0.386	0.683	0.363	0.751		
PE	0.527	0.644	0.510	0.604	0.827	

Source: Primary Data calculated by utilising SmartPLS 3

*AI- Adoption Intention, PEJ- Perceived Enjoyment, EE- Effort Expectancy, ANT- Anthropomorphism,

PE- Performance Expectancy, PT- Perceived Trust

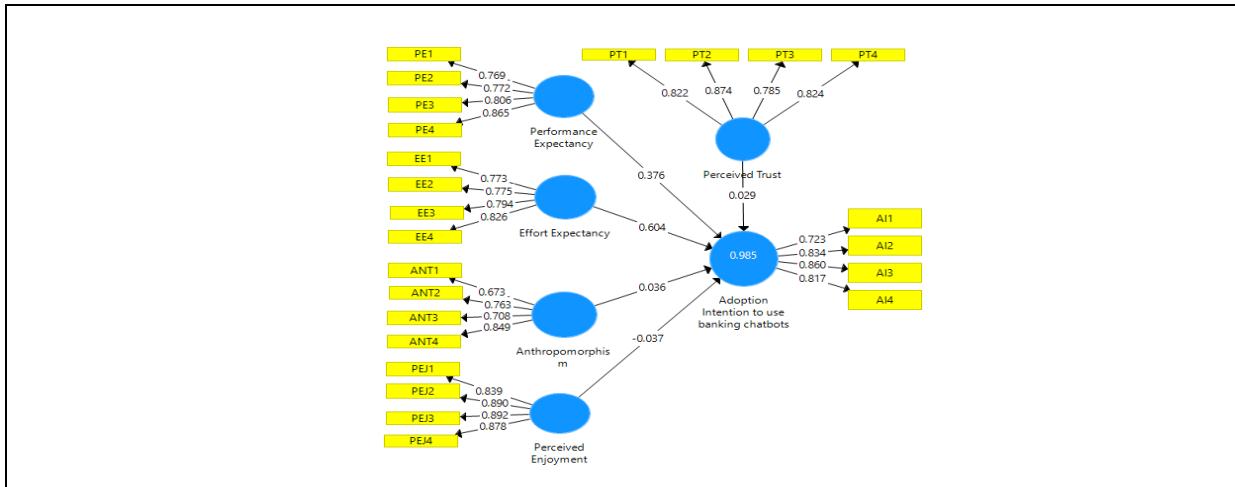


Fig 2 PLS algorithm results

Source: Primary Data calculated by utilising SmartPLS 3

Discussion

This study expands the insight into the role of Anthropomorphism, Effort expectancy, Performance expectancy, Perceived trust and perceived enjoyment among banking chatbot adoption intention of banking customers. This study found that effort expectancy was the strongest variable that influenced the adoption intention to use banking chatbots in India. Followed by, performance expectancy that significantly impacted the adoption intention of banking chatbots. Furthermore, perceived enjoyment has a strong impact towards the adoption intention to use banking chatbots. The above three factors also showed t-value is higher than 1.96, which finalises that H1, H2, and H5 are acceptable. Meanwhile, anthropomorphism and perceived trust had less influence towards the adoption intention to use banking chatbots in India. Thus H3 and H4 are not predominant. The results of the study agree with the previous research findings, like the impact of performance expectancy and effort expectancy and partially agree with perceived trust, perceived enjoyment and anthropomorphism. Banking chatbots provide rapid customer support rather than contacting the bank customer representative, which consumes more time. So, chatbot reduces time consumption and efficiently increases performance. Together with raising consumer usage, this will also promote customer loyalty and retention. Customers can easily conduct transactions using speech or text with the assistance of banking chatbots. Moreover, compared to traditional banking methods, getting services through a chatbot is simple. Chatbots can easily incorporate websites, mobile applications and conversational platforms. So due to inter-linkage between the various platforms, it is easy to access and get information through chatbots. Using chatbots also provides a hedonic feeling among customers. Due to its game-like content like talking, instant replay and stuff like engaging the customers with the chatbots. For instance, Banks are continually developing new campaigns and customised financial plans for their customers. Chatbots can help customers to find the right products for them and get information. Most of the customers are using the text or text and voice option rather than voice only to avoid misunderstanding. Even though chatbot provides information like humans, it still struggles to understand some customers' queries, which results in impertinent conversation. Hence, anthropomorphism and perceived trust have less impact on the adoption intention of banking chatbots among banking customers.

Policy Implication

Banks should make the customers aware of the banking chatbot service and create trust in this service, just like making an ATM card familiar among its customers two decades ago. Another important issue in using a banking chatbot is a misunderstanding of natural language by the machine. So, banks should consider the issue and fix this in future. Banks can benefit from chatbots because they can lower operating expenses and boost satisfaction of customers by simplifying conversations. Yet because this is a new technology, banks are recommended to use tried-and-true methods to protect their reputation from chatbot errors. Banking has enormous stakes, unlike any other industry that uses Chatbots. The Chatbot offerings by banks must be quite extensive and growing as a pivotal channel. In the instance of banks deploying chatbots in India, the expense of fixing a mistake is outrageously costly. Hence bank has to design the bots efficiently to attract customers and reduce bankers' extensive workload. These trends in banking technology will continue to transform how banks engage with customers and organisations throughout the world. Apart from the exposure influencing our acceptance of banking chatbots' position in banking, the technology itself is constantly improving.

Limitation

There are numerous limitations when it comes to obtaining information from banking consumers. Additionally, this study was only conducted in the Indian state of Tamil Nadu. Generally, customers are hesitant to share their responses leads to limited responses for this study. Some of the tech-savvy banking customers frequently use banking chatbots, and still, many customers are hesitant to use them. Sometimes chatbots struggle to perform complicated tasks correctly, which results in providing irrelevant information. Customers expect financial services that are personalised to their specific requirements and provided at their comfort in today's emerging world. The COVID-19 epidemic, which has hastened the transition to digital banking, has amplified this anticipation. Banks must offer seamless, individualised digital interactions across a variety of channels and platforms, including chatbots, social media, and mobile apps, to satisfy this demand.

Conclusion

This study proposes and examines the extended UTAUT model for banking chatbots in India, providing insight into how users effectively adopt chatbots. Customers who use banking chatbots want them to be simple to use and to answer to their inquiries as quickly as possible; otherwise, their experience will be negatively impacted. All age groups are seeing an upsurge in interest for mobile banking. Chatbots that are embedded into mobile apps and are always available can provide users with quick fixes for priority issues that they are unable to handle through the app. Customers favour texting. Instagram, Telegram and WhatsApp are among the messaging apps that almost every users of mobile are connected with. Particularly among millennials, verbal as well as written communication via those applications is favoured. These well-known texting services are also being tested by banks for customer support. To achieve this, the designers must make sure that the chatbots have access to enough information by equipping them with it. Since chatbots are a rapidly developing service technology, their usefulness improves over time as they handle a variety of user queries submitted in various formats. Moreover, Customers generally anticipate excellent availability and dependability from the chatbots. This is essential because banks spend a great deal of money in the establishment of emerging technologies and must make sure that their investments are yielding a reasonable return. Further, if customers learn how to use the chatbots, customer support expenses for banks might drop dramatically, thereby improving revenue. Banks can employ a variety of AI implementation techniques in their business operations. Big data, cloud infrastructure, and python modules have all been recommended as vital components for IT infrastructure. Partnership with FinTech firms may also contribute to the efficient and cost-effective implementation of digital banking.

References

Adamopoulou, EALM 2020, 'An overview of chatbot technology, *In IFIP International Conference on Artificial Intelligence Applications and Innovations*, Springer.

Alalwan & Dwivedi 2017, 'Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust', *Int. J. Inf. Manag.*, p. 99–110.

Alshare, MA 2014, 'The moderating effect of espoused cultural dimensions on consumer's intention to use mobile payment devices', *35th Int. Conf. Inf. Syst.*, p. 1–15.

Araujo, T 2018, 'Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions', *Computers in Human Behavior*, 85, p.183-189.

Baabdullah, AM, AAA, RNP, KH,&PP 2019, 'Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model', *International Journal of Information Management*, 44, p. 38-52.

Bao, H, Li, B, Shen, J & Hou, F 2016, 'Repurchase intention in the Chinese e-marketplace', *Ind. Manag. Data Syst.* 116, p. 1759–1778.

Bartneck 2009, 'Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence and perceived safety of robots, *International journal of social robotics*, 1(1): p. 71- 81.

Brachten 2021, 'The acceptance of chatbots in an enterprise context—A survey study, *International Journal of Information Management*, vol 60, p. 102-375.

Brown & Venkatesh, V 2005, 'Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle, *MIS quarterly*, p. 399-426.

C. Kim, MMIL 2010, 'An empirical examination of factors influencing the intention to use mobile payment', *Comput. Hum. Behav.* 26 (3), p. 310–322.

Childers, TL, CCL, PJ,&CS 2001, 'Hedonic and utilitarian motivations for online retail shopping behaviour', *journal of retailing*, 77(4), p. 511-535.

De Graaf, MM, AASB 2013, 'Exploring influencing variables for the acceptance of social robots, *Robotics and Autonomous Systems*, 61(12), p. 1476-1486.

Epley, N, WA,&CJT 2007, 'On seeing human: a three-factor theory of anthropomorphism', *Psychological Review*, 114(4), p. 864.

Fang, Y, Qureshi, I, Sun, H, McCole, P, Ramsey, E & Lim, KH 2014, 'Trust, satisfaction, and online repurchase intention', *Mis Q.*

Fornell, C,&LDF 1981, 'Evaluating structural equation models with unobservable variables and measurement error', *journal of marketing research*, vol 18, no. 1, p. 39-50.

G.W.H. Tan 2014, 'NFC mobile credit card: the next frontier of mobile payment?', *Telematics Inf.* 31 (2), p. 292–307.

Ghalandari, K 2012, 'The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: The moderating role of age and gender. *Middle-East Journal of Scientific Research*.

Hair JF, 2014, 'A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)', *Sage Publications*.

Handarkho 2019, 'Intention to adopt mobile payment in physical stores: Individual switching behaviour perspective based on Push–Pull–Mooring (PPM) theory ', *Journal of Enterprise Information Management*.

Hayashi, F,&BT 2014, 'Mobile payments: Merchants' perspectives', *Economic Review*, 99, p. 5-30.

Hwang, S,&KJ 2021, 'Toward a Chatbot for Financial Sustainability', *Sustainability*, 13(6), p. 3173.

I. Ha, YYMC 2007, 'Determinants of adoption of mobile games under mobile broadband wireless access environment', *Inf. Manag.*, vol 44, no. 3, p. 276–286.

Jambulingam, M 2013, 'Behavioural intention to adopt mobile technology among tertiary students' *world applied sciences journal*, 22(9), p. 1262-1271.

Jang, M, JY,&KS 2021, 'Investigating managers' understanding of chatbots in the Korean financial industry.', *Computers in Human Behavior*, 120, p. 106747.

K. Rouibah, PBLYH 2016, 'The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country, *Electronic Commerce Research and Applications*.

Kasilingam, DL 2020, 'Understanding the attitude and intention to use smartphone chatbots for shopping', *Technology in Society*, 62, 1, p. 01280.

Kuberkar, S,&STK 2020, 'Factors Influencing Adoption Intention of AI-Powered Chatbot for Public Transport Services within a Smart City', *International Journal of Emerging Technologies in Learning*, 11(3), p. 948-958.

Liébana-Cabanillas, F, MV, DLIR,&KZ 2018, 'Predicting the determinants of mobile payment acceptance: A hybrid SEM-neural network approach.' *Technological Forecasting and Social Change*, p. 117-130.

Luhmann, N 1979, 'Trust and Power', *John Wiley and Sons: Chichester*, UK.

Mogaji, E, BJ, NAC,&NNP 2021, 'Emerging-Market Consumers' Interactions with Banking Chatbots', *Telematics and Informatics*, p. 101711.

Nguyen, DM, CYTH,&LHD 2021, 'Determinants of Continuance Intention towards Banks' Chatbot Services in Vietnam: A Necessity for Sustainable Development.', *Sustainability*, 13(14), p. 7625.

Pal, SN,&SD 2019, 'Chatbots and virtual assistant in Indian banks', *Industrija*, 47(4), p. 75-101.

Sarfaraz, J 2017, 'Unified theory of acceptance and use of technology (Utaut) model-mobile banking.', *Journal of Internet Banking and Commerce*, 22(3), p.1-20.

Sheehan, B, JHS, AGU 2020, 'Customer service chatbots: Anthropomorphism and adoption.', *Journal of Business Research*, 115: p.14-24.

Singh, N & Neena, S 2020, 'How perceived trust mediates merchant's intention to use a mobile wallet technology', *Journal of Retailing and Consumer Services*.

Slade, E & Michael, W 2014, 'Exploring consumer adoption of proximity mobile payments', *Journal of Strategic Marketing*, p. 1-15.

Slade, EL, Williams, MD & Dwivedi, YK 2013, 'Mobile payment adoption: Classification and review of the extant literature.', *Mark. Rev.*13, p. 167–190.

Sugumar, M,&CS 2021, 'Do I Desire Chatbots to be like Humans? Exploring Factors for Adoption of Chatbots for Financial Services', *Journal of International Technology and Information Management*, 30(3), p. 38-77.

Suhel, SF, SVK, VS,&MVP 2020, 'Conversation to Automation in Banking through Chatbot Using Artificial Machine Intelligence Language.', In 2020 8th International Conference on Reliability, Infocom Technologies and Optimization, IEEE.

T. Teo 2009, ' Is there an attitude problem? Reconsidering the role of attitude in the TAM,' *Br. J. Educ. Technol.*, vol 40, no. 6, p. 1139–1141.

Thong, JY, HSJ,&TKY 2006, 'The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance', *International Journal of human-computer studies*, 64(9), p. 799-810.

Trivedi, J 2019, 'Examining the customer experience of using banking chatbots and its impact on brand love: the moderating role of perceived risk', *Journal of Internet Commerce*, 18(1), p. 91-111.

V. Venkatesh, MMGDAFD 2003, 'User acceptance of information technology: Toward a unified view', *MIS Q.*, vol. 27, no. 3, p. 425–478.

V. Venkatesh, JYLTA 2012, 'Consumer acceptance and use of information technology: Extending the unified theory', *MIS Q.*, vol. 36, no. 1, p.157–178.

Van der Heijden, H 2004, 'User acceptance of hedonic information systems.', *MIS quarterly*, p. 695-704.

Venkatesh, V,&DFD 2000, 'A theoretical extension of the technology acceptance model: Four longitudinal field studies. ', *Management Science*, vol 46, no. 2, p.186-204.

Venkatesh, V,&BH 2008, 'Technology acceptance model 3 and a research agenda on interventions. ', *Decision sciences*, vol 2, no. 273-315., p. 39.

Venkatesh, V & Thong, JY 2011, 'Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context.', *Inf. Syst. J.* 21, p. 527–555.

Wagner, K, NF,&S-KH 2019, 'Is it human? The role of anthropomorphism as a driver for the successful acceptance of digital voice assistants. ', In *Proceedings of the 52nd Hawaii international conference on system sciences*.

Waterman, C 2018, "Consumer Online Banking Trends 2018", viewed 30 September 2021, <<https://humleyai.com/2018/09/18/consumer-online-bankingtrends-2018/>>.

Wilson-Evered, CA 2012, "Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT", *Comput. Human Behav.*, vol. 28, no. 6, p. 2034–2045.

Zhou, T 2013, ' An empirical examination of continuance intention of mobile payment services.', *Decision support systems*, vol 54, no. 2, p. 1085-1091.

Zhou, T 2014, 'An empirical examination of initial trust in mobile payment. ', *Wirel. Pers. Commun.*, 77, p. 1519–1531.