Journal of Commerce and Accounting Research
14 (4) 2025, 55-64
www.publishingindia.com/jcar/
https://doi.org/10.21863/jcar/2025.14.4.006

Submitted: 09 June, 2024
Accepted: 18 November, 2024

CHATBOTS ADOPTION BEHAVIOUR IN BANKING: AN EMPIRICAL STUDY IN SOUTH INDIA

D. Kesavan*, S. Sivaprakkash, N. Marianand*****

Abstract *The digital transformation has impacted all sectors, including banking, and has led to adopting Artificial Intelligence (AI) to improve services and operational efficiency. Driven by artificial intelligence, banks increasingly use chatbot applications to provide quick, efficient, and error-free services, resulting in increased revenues. This study aimed to investigate the determinants of Behavioural Intention to Use (BTU) chatbots in banking using an Empirical Research Design with a sample of 800 respondents from five public and five private sector banks in the South Indian states. The study found that perceived usefulness and ease of use directly influence behavioural intention to use chatbots, while perceived trust has a significant indirect effect. Awareness of Service (AWS) and perceived compatibility also have a substantial indirect impact on behavioural intention to use chatbots, and Perceived Ease of Use (PEU) is the critical factor in the adoption of chatbots in banking; consumers expect chatbots to be helpful, easy to use, compatible with their lifestyle, and accompanied by clear communication on their usage and benefits. Banks can leverage these findings to improve the design and implementation of chatbots and communicate their benefits to customers to enhance their acceptance and usage.*

Keywords: *Artificial Intelligence, Banking, Behavioural Intention, Chatbot, Consumer Intention*

JEL Classification: *E50, G20, M15*

INTRODUCTION

Digital transformation influences every segment and company to a higher extent (Schwab, 2016). Digital media's influence defines the drivers of the software economy, focusing on technological advancements to enrich customer service efficiency (Salisu & Bakar, 2020). Artificial Intelligence (AI) has improved business transactions and services, driving companies to develop advanced business models with the help of technological innovation (Koehler, 2018). AI can assist companies seeking technological rejuvenation, high competitiveness, and operational productivity (Brill et al., 2022). The use of AI in chatbot applications enhances service competence by being quick and assertive, economical, accessible and available (Maedche et al., 2019), and the banking sector is not an exception.

Banks employ AI on a large-scale level to survive in the competitive market (Biswas & Carson, 2020). By customising its services, AI increases bank revenues (Agarwal, 2019). It increases the efficiency of banks and lowers the overall cost while reducing errors in service deliveries (Trivedi, 2019).

Chatbot Technology in Banking

The chatbot application is a computer program that imitates human conversations using natural structures such as Natural Language Processing (NLP), image and video processing and audio analysis (Bala et al., 2017). In the banking industry, chatbots are used to manage financial operations such as reviewing accounts, communicating lost cards or delivering payments, renewing a policy or managing a refund (Tarbal, 2020). The factors influencing the use of chatbots in banking depend on perceived usefulness, ease of use, compatibility, and perceived risk in chatbots (Sarbabidya & Saha, 2020). The usage of chatbot technology in the Indian banking sector is continuously growing (Gupta & Sharma, 2019).

* Assistant Professor, Faculty of Management, SRM Institute of Science & Technology, Kattankulathur Campus, Tamil Nadu, India. Email: dhakshanasri2015@gmail.com

** Assistant Professor, Department of Commerce, Central University of Tamil Nadu, Thiruvarur, Tamil Nadu, India. Email: ssivaprakkash@gmail.com (Corresponding author)

*** Associate Professor, Department of Business Studies, University of Technology and Applied Sciences, Salalah, Oman. Email: n.marianand@gmail.com

Background of the Study

Banks must make every effort to assist their customers in adopting internet banking, thereby increasing their loyalty and confidence (Sidhu, 2018). Cardona et al. (2019) and Quah and Chua (2019) focused on the level of chatbot usage in the banking industry. They found that the usage level is not at maximum, but the intention to use is increasing. Richad et al. (2019) found that the level of innovation, perceived usefulness, perceived ease of use, and attitude toward using chatbots having a significant positive impact on the intention to use this technology. Sarbabidya and Saha (2020) revealed the role of chatbot technology in customer services in the banking industry, such as advisory services, convenient services, cost-effective services, customer-friendly services, relationship banking services and trustworthy services. Sayiwal and Alankar (2020) identified the key function of chatbots in banking as a conversational interface, financial advice and 24*7 digital support.

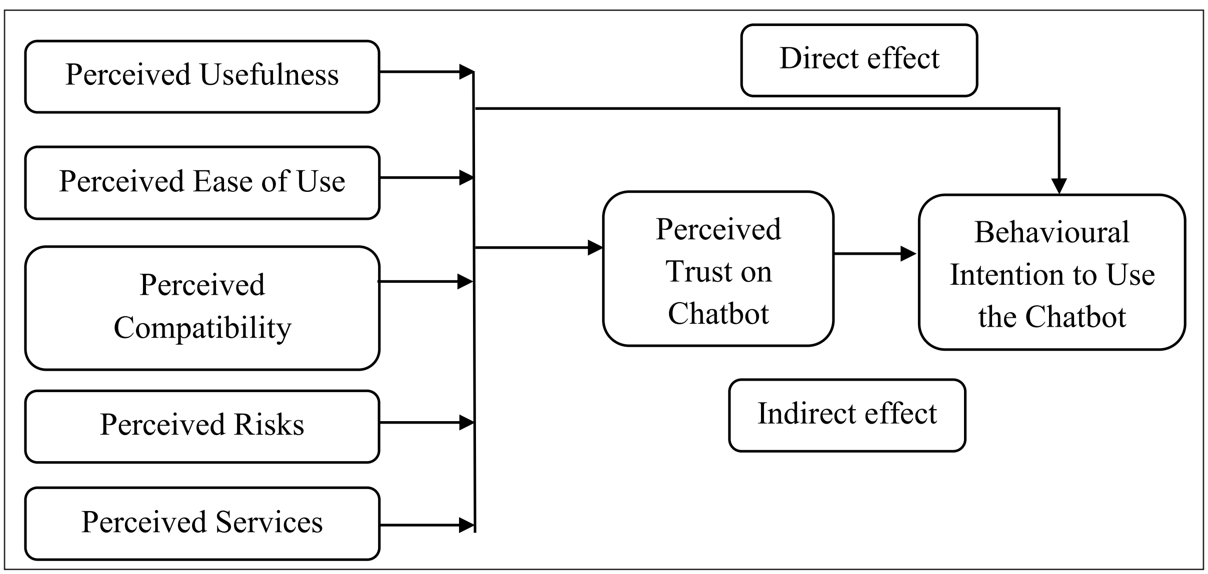
Based on the reviewed literature, many studies attempt to measure the level of chatbot usage in banking and only a few focus on the factors that lead to the usage of chatbots. Only limited studies discussed the behavioural intention to use chatbots shortly. However, studies have yet to attempt to identify the link between these constructs, namely determinants of usage of chatbots, perceived trust in them, and intention to use them soon. Since the study is essential for future policy implications, the research focuses on these aspects with specific objectives.

RESEARCH OBJECTIVES

- To study customer's view on the determinants of the usage of chatbots in banking.
- To measure the level of perceived trust in chatbots and the intention to use them in the near future.
- To evaluate the linkage between these three constructs.

CONCEPTUAL FRAMEWORK

The study starts with conceptual development to fulfil the objectives.



Source: Developed by the authors.

Fig. 1: Hypothesised Framework

The concepts used in the present study are explained below:

Perceived Usefulness (PU)

Perceived usefulness shows the level of perception of the new system's utility (Davis, 1989). It is the performance expected from the usage of a system (Li & Kishore, 2006). In the case of banking, various types of virtual banking are adopted because of their expected performance (Safeena et al., 2012). Perceived usefulness has a significant impact on adopting new technology in banking (Alalwan et al., 2018). While perceived usefulness among male participants is influenced by relative advantage, trust, and yearly income, Perceived Ease of Use (PEU) in female participants is influenced by perceived cost and value compatibility (Changati & Kansal, 2019).

Perceived Ease of Use (PEU)

Perceived Ease of Use (PEU) influences people's technology adoption level (Aggarwal & Patel, 2023). It is defined as the ease of use of a system free from many doubts (Farah et al., 2018). It strongly drives behavioural intention to use technology (Giovanis et al., 2019). The ease of using a particular or new system in online banking results in higher usage (Martins et al., 2014). PEU leads to perceived usefulness, which impacts a positive behavioural intention to use online banking (Tom & Krishnan, 2021). Even if a person is sufficiently literate and self-assured to adjust to a new system, they will revert to the old method if the technology does not allow them to complete their transactions (Fig. 1). Higher PEU is typically associated with a more significant relative advantage offered by the technology, with higher discomfort corresponding to lower PEU and vice versa (Changati & Kansal, 2019).

Perceived Compatibility (PC)

Perceived compatibility represents the new system's perceived consistency with the values, past experiences, and needs of potential future adopters (Roger, 1983). The higher adoption rate of any system rests on the compatibility of the new system with an individual's lifestyle (Koenig-Lewis et al., 2010).

Perceived Risks (PR)

To mitigate risks, banks must equip themselves with the newest technologies and attempt to address the numerous security challenges (Sidhu, 2018). Perceived risk refers to the risk consumers perceive when using new systems (Arif et al., 2006). In the case of banking, perceived risk represents the level of risk perceived in online banking usage among consumers, leading to their intention to use it soon (Kolodinsky et al., 2004). Moreover, perceived risk indirectly impacts the behaviour of intention to use the chatbots (Shankar & Kumari, 2016). PEU is influenced by perceived risk; the higher the perceived risk, the lower the perceived ease of use, and vice versa. This holds true even when the relative advantage provided by the technology is generally minimal (Changati & Kansal, 2019).

Awareness of Service (AWS)

The level of awareness indicates the extent of information regarding availability, usage patterns and other aspects related to the adoption of chatbots in the banking sector (Al-Somali et al., 2009). The higher level of awareness of online banking results in higher adoption (Pikkarainen et al., 2004).

Perceived Trust (PT)

The perceived trust refers to trust in technology as customers expect it to be technically competent, reliable and dependable effectiveness in the technology they are willing to use (Khan, 2018). Accepting and adopting new technology is critical (Yiga & Cha, 2016). It is the most influencing variable in identifying the achievement of e-banking services (López-Miguens & Vázquez, 2017). People are satisfied with digital banking and expect a dedicated centre for grievance resolution, which enhance customer happiness (Subrahmanyam et al., 2021).

Behavioural Intention to Use (BTU) the Chatbot

Behavioural Intention to Use (BTU) is defined as an individual's intention to use the system both currently and in the future (Venkatesh et al., 2003). It reflects respondents' mindset in using online banking (Davis, 1989). It is the collection of the various outcomes, namely liking, willingness, interest and intention to use the aspect (Gefen et al., 2003). The variables related to the seven constructs are given in Table 1.

Table 1: Variables in Seven Constructs (SC)

Sr. No.	Factors in Seven Constructs	Sr. No.	Factors in Seven Constructs
I	**Perceived Usefulness (Richad et al., 2019)**	**V**	**Awareness of Services (Hanafizadeh and Khedmatgozar, 2012)**
1	Knowing the usefulness of chatbots in daily life	1	Communication on chatbot usage of policy
2	The use of chatbot led to time savings	2	Clarity in the strategy to use chatbot
3	The use of a chatbot results in quick completion of work	3	Sufficient information on chatbot
4	The use of chatbots increases productivity	4	Recommendation from my bank to use a chatbot
5	The use of a chatbot extends the scope of achievements	5	Continuous supply of information on the bank's chatbot services

Sr. No.	Factors in Seven Constructs	Sr. No.	Factors in Seven Constructs
II	**Perceived Ease of Use (Akturan & Tezcan, 2012)**	**VI**	**Perceived Trust on Chatbot (Wen et al., 2019)**
1	Easy to learn chatbot	1	Trust in chatbot technology
2	Easy to implement chatbot	2	Trust in the competency of chatbot
3	Easy to interact through chatbot	3	Trust in the reliability of chatbot services
III	**Perceived Compatibility (Kolodinsky et al., 2004)**	4	Trust in the performance of chatbot
1	Chatbots fit with my lifestyle	5	Trust in the competitive advantage of chatbot
2	Chatbots fit well to interact with companies	**VII**	**Behavioural Intention to Use the Chatbot (Schierz et al., 2010)**
3	Chatbot usage gives better hope of pleasure	1	Use of chatbot wherever essential
4	Chatbot needs of potential adopters	2	Likely to use a chatbot soon
IV	**Perceived Risks (Trivedi, 2019)**	3	Increase the frequency of usage of chatbot
1	Misuse of privacy information	4	Intention to suggest others on chatbot
2	Inappropriate sharing of information	5	Comfortable using chatbot
3	Privacy could be exposed		
4	Personal information could be intercepted		

RESEARCH METHODOLOGY

The applied research design of the study is a mix of descriptive and diagnostic designs since the analysis is based on the customers' view on chatbots in banking and the cause-and-effect relationship between the drivers of BTU chatbots among the customers. The study's sample size is decided by the formula of $n = \left[\frac{Z\sigma}{D}\right]^2$ whereas n-sample volume and the z-z value at a five-point scale, σ-standard deviation of customer satisfaction on chatbot at pilot study (variable is measured at five-point Likert scale) and e-error of acceptance. It came to 800 respondents.

The study covers five public sector banks and five private sector banks in the headquarters of the South Indian states of Tamil Nadu, Andhra Pradesh, Telangana, Karnataka and Kerala. From each bank, sixteen chatbot users were identified with the help of the concerned branch manager. The required primary data are collected through the pre-tested questionnaire. The responses to the questionnaire sent to the sampled respondents in three successive attempts in total comes to 69.13 (553÷800) per cent to the total of 800 respondents. The collected data are processed with the help of appropriate statistical analysis.

RESULTS AND DISCUSSION

The demographic profile of the respondents was illustrated using descriptive statistics. The dominant gender among them was male, whereas the most dominant age group was 25 to 35 years. The dominant level of education among them was under graduation and above, whereas the dominant occupation level was business and allied fields. The dominant field of work among them was service-related activities. Most of the respondents are used m-banking. They used their mobile phone for the chatbot banking activities. The most dominant account they keep is a savings account. The dominant years of experience in using chatbots is more than one year.

Validation of the Constructs Developed for the Study

The present study included seven constructs: perceived usefulness with five variables; PEU with three variables; perceived compatibility and perceived risks, each with four variables; awareness of services, perceived trust and behavioural intention to use, each with five variables. The initial analysis confirmed the validity of the variables included in each construct with the assistance of Confirmatory Factor Analysis (CFA) and Cronbach's Alpha.

The internal consistency, content validity, discriminant validity and convergent validity were tested (Ringle et al., 2013). The results of CFA and Cronbach's Alpha are shown in Table 2.

Table 2: Psychometric Properties of the Constructs

Sr. No.	Construct	Range of Standardised Factor Loading	Composite Reliability	Average Variance Extracted	HTMT Ratio	Cronbach's Alpha
1	Perceived Usefulness	0.8919*-0.6447*	0.7802	54.51	0.7814	0.7644
2	Perceived Ease of Use	0.9092*-0.6241*	0.7964	55.49	0.8022	0.7742
3	Perceived Compatibility	0.8914*-0.6024*	0.7545	52.96	0.6414	0.7343
4	Perceived Risks	0.8806*-0.6593*	0.7702	53.97	0.7045	0.7503
5	Awareness of Services	0.9117*-0.6743*	0.8142	56.08	0.7141	0.7997
6	Perceived Trust on Chatbot	0.8901*-0.6542*	0.7749	54.03	0.6886	0.7602
7	Behavioural Intention to Use the chatbot	0.8664*-0.6848*	0.7674	52.42	0.6911	0.7401
* Significant at 5% level						

Source: Primary data was collected through a questionnaire and analysed in SPSS.

The content validity of all seven constructs has been proved since the standardised factor loading of variables in each construct is greater than 0.60. The convergent validity is confirmed in all constructs since it is aggregate consistency and the standard variable extracted are higher than 0.50 and 50.00 per cent, respectively (Hanafizadeh & Khaematgozar, 2012). The Heterotrait Monotrait Ratio (HTMT) of all constructs (interrelation and coefficient between the constructs) is less than its minimum threshold of 0.85 (Henseler et al., 2018). The overall reliability in each construct is proven since its Cronbach's Alpha is higher than 0.70.

Measurement of the Constructs in the Study

The mean score of each construct examines the respondents' views on the seven constructs. The mean value of the factors in each construct determines the magnitude of each construct. The standard deviation and coefficient of variation of each construct are also measured and presented in Table 3.

Table 3: Measurement of the Constructs

Sr. No.	Constructs	Mean Score	SD	Co-Efficient of Variation
1	Perceived Usefulness	3.8142	0.4796	12.57
2	Perceived Ease of Use	3.7908	0.4173	11.01
3	Perceived Compatibility	3.7141	0.4786	12.89
4	Perceived Risks	-3.0114	0.6088	20.22
5	Awareness of Services	3.6441	0.5869	16.10
6	Perceived Trust on Chatbot	3.2469	0.4022	12.38
7	Behavioural Intention to Use the chatbot	2.9974	0.6441	21.49

Source: Primary data was collected through a questionnaire and analysed in SPSS.

The highly viewed independent constructs by the respondents are perceived usefulness and perceived ease of use, with a mean of 3.8142 and 3.7908, respectively. The respondents noticed greater consistency in their views on perceived ease of use, with a coefficient of variation of 11.01%. The perceived trust among the respondents is only at a moderate level since its mean value is 3.2469. The level of BTU is lower, with a mean score of 2.9974. The level of BTU chatbot technology is less than the level of perceived trust in banking.

The Linkage Between the Determinants, Behavioural Intention to Use Chatbots and Perceived Trust in Chatbots

The present analysis examines the linkage between the determinants and BTU chatbots through perceived trust. Structural equation modelling has been adopted to evaluate the linkage through the direct and indirect effects of determinants, whereas perceived trust act as the mediator variable (Bollen & Scott, 1993). Initially, the model fit was been estimated by examining the fit indices (Bentler & Bonett, 1980). The fit indices are summarised in Table 4.

Table 4: Fit Indices of Structural Equation Modelling

Sr. No.	Tests	Actual Value	Standard Value	Result
1	Goodness of Fit (GFI)	0.9544	≥ 0.90	Valid
2	Adjusted Goodness of Fit Index (AGFI)	0.9401	≥ 0.90	Valid
3	Root Mean Residual (RMR)	0.0302	≤ 0.05	Valid
4	Root Mean Square Error Approximation (RMSEA)	0.0297	≤ 0.05	Valid
5	Normed Fit Index (NFI)	0.9245	≥ 0.90	Valid
6	Relative Fit Index (RFI)	0.9676	≥ 0.95	Valid
7	Comparative Fit Index (CFI)	0.9344	≥ 0.90	Valid
8	Tucker Lewis Index (TLI)	0.9379	≥ 0.95	Valid
9	Significance of Chi-Square Statistics	0.0174	≤ 0.05	Valid

Source: Primary data was collected through a questionnaire and analysed in SPSS.

The Table 4 shows that fit indices satisfy the respective standard levels. The GFI and AGFI are higher than 0.90, whereas the RMR and RMSEA are lower than 0.05. The NFI and RFI are higher than 0.90 and 0.95, respectively. The CFI and TLI are greater than 0.90 and 0.95, respectively. The significance of the chi-square score is considerable at a two per cent level. All these results indicate the validity of the fitted path model developed using SEM.

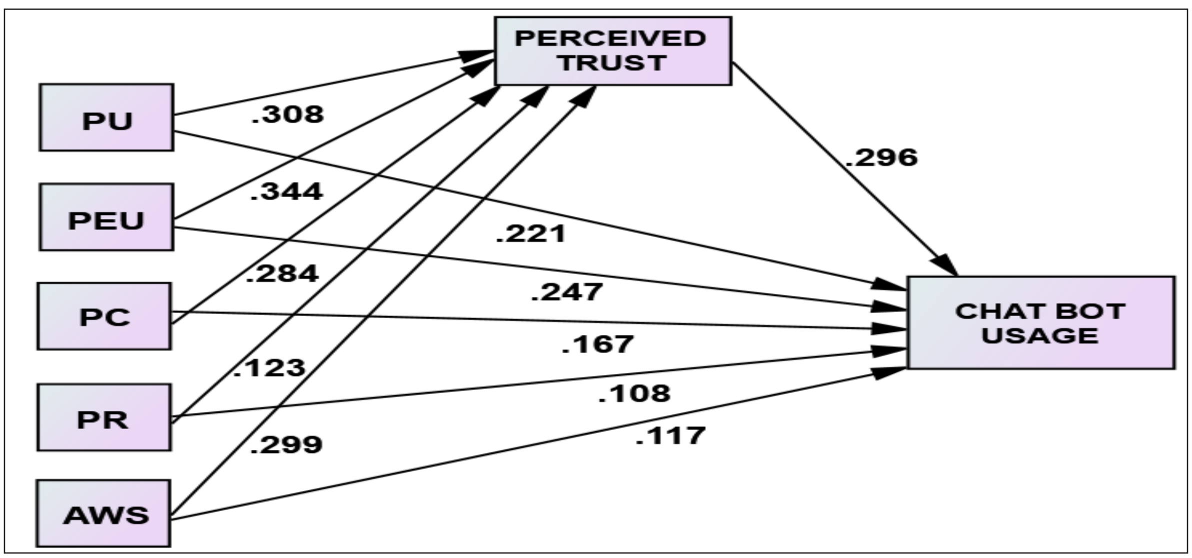


Fig. 2: Structural Equation Model of Direct Effect and Indirect Effect (A Path Model of the Relationship Between the Key Constructs)

Direct, Indirect Path Co-Efficient of Determinants to Use Chatbots

The executed SEM results show the direct and indirect path co-efficients of determinants of the chatbots usage, as well as their statistical significance and total effect. The results are summarised in Table 5.

Table 5: Indirect, Direct, and Total Effects of Determinants of Usage of Chatbots

Sr. No.	Construct	Direct Effect	Indirect Effect	Total Effect
1	Perceived Usefulness	0.2214*	0.3084*	0.5298
2	Perceived Ease of Use	0.2473*	0.3441*	0.5914
3	Perceived Compatibility	0.1676	0.2842*	0.4518
4	Perceived Risks	-0.1084	-0.1233	-0.2317
5	Awareness of Services	0.1179	0.2994*	0.4173
6	Perceived Trust on Chatbot	0.2969*	-	-
	Total	0.6458	1.1128	1.7586

Dependent variable: Behavioural Intention to Use the Chatbot
Mediator variable: Perceived Trust on Chatbot
* Significant at 5% level.

Source: Primary data was collected through a questionnaire and analysed in SPSS.

The SEM shows that the significant direct effect on BTU chatbots is perceived usefulness and PEU since their direct effects are considerable at a five per cent level. However, the indirect effects are contributed by perceived usefulness, perceived ease of use, perceived compatibility, and AWS since its indirect path coefficient is statistically significant. The higher total effect is made by PEU and perceived usefulness since its total effects are 0.5914 and 0.5298, respectively. Perceived trust has a significant direct effect on behavioural intention to use, whereas perceived risks have no significant indirect or direct effect on behavioural intention to use. The total indirect effect is higher than its direct effect since its total effects are 1.1128 and 0.6458. The above-said results indicate the significant mediating function of perceived trust between determinants of BTU and intention to use chatbots in banking.

DISCUSSION OF RESULTS

The current study recognises two crucial factors that directly influence BTU chatbots: perceived usefulness and perceived ease of use, replicating the findings of (Venkatesh & Davis, 2000). Perceived trust has a significantly direct solid impact on BTU chatbots since its direct effect is 0.2969, which is like the findings of (Farah et al., 2018). The higher total indirect effect compared to the total direct effect made by the determinants on the BTU chatbots recalls the findings of Martins et al. (2014). The significant mediator role perceived trust play is similar to the findings of Shankar and Kumari (2006). The highly significant indirect effect of AWS on behavioural intention through perceived trust aligns with the findings of Al-Somali et al. (2009). Therefore, a high PEU is critical in banking chatbot adoption through the perceived risk.

Managerial Implications

The significant direct and indirect consequences of perceived usefulness and PEU on behavioural intention indicate that the consumers expect both utility and comfortableness in using chatbots. The role of perceived compatibility and AWS create a significant indirect effect on behavioural intention. Hence, consumers are expecting more compatibility with their lifestyles from the use of chatbots and expecting much information about their usefulness. Since perceived trust significantly influences the intention to use chatbots, the banks are advised to focus on enriching the perceived trust among the customers. This will automatically resolve a rise in the BTU chatbots.

CONCLUSION

The present study identifies five critical drivers of BTU chatbots in banking: perceived usefulness, perceived ease of use, perceived compatibility, perceived risk and awareness of service. The first two determinants that contribute most to the intention to use chatbots are PEU and perceived usefulness, followed by perceived compatibility. Perceived risk does not directly or indirectly contribute significantly to the intention to use chatbots. The higher total indirect impact on BTU chatbots reveals the significant role of perceived trust in enriching the intention to use them. Hence, the study concluded that if the determinants initially focus on creating perceived trust among the customers, the BTU chatbots will be significantly higher.

Authors' Contribution

The idea for this paper was developed by Dr. D. Kesavan and Dr. N. Marianand, who framed the research design for the paper. Dr. S. Sivaprakkash extracted the relevant research papers and prepared the Review of Literature. Dr. D. Kesavan and Dr. S. Sivaprakkash constructed the questionnaire and collected and processed the data for analysis. The analyses and interpretations of the data were done by Dr. D. Kesavan using SPSS. Dr. S. Sivaprakkash and Dr. N. Marianand wrote the manuscript.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organisation or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgement

The authors received no financial support for the research, authorship, or publication of this article.

REFERENCES

Agarwal, P. (2019, March). Redefining banking and financial industry through the application of computational intelligence. *Advances in Science and Engineering Technology International Conferences (ASET)* (pp. 1–5). IEEE. doi:https://doi.org/10.1109/ICASET.2019.8714305

Aggarwal, A., & Patel, M. (2023). Understanding consumer acceptance of e-commerce payment services and banking services: An empirical analysis. *Journal of Commerce and Accounting Research, 12*(4), 32–43.

Akturan, U., & Tezcan, N. (2012). Mobile banking adoption of the youth market: Perceptions and intentions. *Marketing Intelligence & Planning, 30*(4), 444–459. doi:https://doi.org/10.1108/02634501211231928

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services, 40,* 125–138. doi:https://doi.org/10.1016/j.jretconser.2017.08.026

Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An investigation into the acceptance of online banking in Saudi Arabia. *Technovation, 29*(2), 130–141. doi:https://doi.org/10.1016/j.technovation.2008.07.004

Arif, I., Afshan, S., & Sharif, A. (2016). Resistance to mobile banking adoption in a developing country: Evidence from modified TAM model. *Journal of Finance and Economics Research, 1*(1), 24-42.

Bala, K., Kumar, M., Hulawale, S., & Pandita, S. (2017). Chat-bot for college management system using AI. *International Research Journal of Engineering and Technology, 4*(11), 2030–2033.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in analysis of covariance of structures. *Psychological Bulletin, 88*(3), 588–606. Retrieved from https://psycnet.apa.org/doi/10.1037/0033-2909.88.3.588

Biswas, S., & Carson, B. (2020). *AI-bank of the future: Can banks meet the AI challenge?* Retrieved from www.mckinsey.com

Bollen, K. A., & Long, J. S. (Eds.). (1993). *Testing structural equation models* (vol. 154). New Delhi: Sage Publication India Private Limited.

Brill, T. M., Munoz, L., & Miller, R. J. (2022). Siri, Alexa, and other digital assistants: A study of customer satisfaction with artificial intelligence applications. In *The Role of Smart Technologies in Decision Making* (pp. 35-70). Routledge.

Cardona, R.D., Weith, O., Schonborn, S., & Breitner, M. H. (2019). A mixed methods analysis of the adoption and diffusion of chatbot technology in the German Insurance Sector, Twenty-fifth Americas Conference on Information Systems, Cancun.

Changati, V., & Kansal, P. (2019). Factors influencing technology acceptance in the banking sector: A binary recursive partitioning approach. *Journal of Commerce and Accounting Research, 8*(1), 68–82.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. Retrieved from https://www.jstor.org/stable/249008

Farah, M. F., Hasni, M. J. S., & Abbas, A. K. (2018). Mobile-banking adoption: Empirical evidence from the banking sector in Pakistan. *International Journal of Bank Marketing, 36*(7), 1386–1413. doi:https://doi.org/10.1108/IJBM-10-2017-0215

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly,* 51–90. doi:https://doi.org/10.2307/30036519

Giovanis, A., Athanasopoulou, P., Assimakopoulos, C., & Sarmaniotis, C. (2019). Adoption of mobile banking services: A comparative analysis of four competing theoretical models. *International Journal of Bank*

Marketing, 37(5), 1165–1189. doi:https://doi.org/10.1108/IJBM-08-2018-0200

Gupta, A., & Sharma, D. (2019). Customers' attitude towards chatbots in banking industry of India. *International Journal of Innovative Technology and Exploring Engineering, 8*(11), 1222–1225.

Hanafizadeh, P., & Khedmatgozar, H. R. (2012). The mediating role of the dimensions of the perceived risk in the effect of customers' awareness on the adoption of internet banking in Iran. *Electronic Commerce Research, 12,* 151–175. doi:https://doi.org/10.1007/s10660-012-9090-z

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43,* 115–135. doi:https://doi.org/10.1007/s11747-014-0403-8

Khan, Y. H. (2018). A short review of the electronic banking system. *Regional and Business Studies, 10*(1), 13–37. doi:https://doi.org/10.33568/rbs.2333

Koehler, J. (2018). Business process innovation with artificial intelligence: Levering benefits and controlling operational risks. *European Business & Management, 10*(1), 55–66. doi:https://doi.org/10.11648/j.ebm.20180402.12

Koenig-Lewis, N., Palmer, A., & Moll, A. (2010). Predicting young consumers' take up of mobile banking services. *International Journal of Bank Marketing, 28*(5), 410–432. doi:https://doi.org/10.1108/02652321011064917

Kolodinsky, J. M., Hogarth, J. M., & Hilgert, M. A. (2004). The adoption of electronic banking technologies by US consumers. *International Journal of Bank Marketing, 22*(4), 238–259. doi:https://doi.org/10.1108/02652320410542536

Li, J. P., & Kishore, R. (2006, April). How robust is the UTAUT instrument? A multigroup invariance analysis in the context of acceptance and use of online community weblog systems. In *Proceedings of the 2006 ACM SIGMIS CPR Conference on Computer Personnel Research: Forty-Four Years of Computer Personnel Research: Achievements, Challenges & The Future* (pp. 183–189). doi:https://doi.org/10.1145/1125170.1125218

López-Miguens, M. J., & Vázquez, E. G. (2017). An integral model of e-loyalty from the consumer's perspective. *Computers in Human Behavior, 72,* 397–411. doi:https://doi.org/10.1016/j.chb.2017.02.003

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., & Söllner, M. (2019). AI-based digital assistants: Opportunities, threats, and research perspectives. *Business & Information Systems Engineering, 61,* 535–544. doi:https://doi.org/10.1007/s12599-019-00600-8

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management, 34*(1), 1–13. doi:https://doi.org/10.1016/j.ijinfomgt.2013.06.002

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. *Internet Research, 14*(3), 224–235. doi:https://doi.org/10.1108/10662240410542652

Quah, J. T., & Chua, Y. W. (2019). Chatbot assisted marketing in financial service industry. In Services Computing-SCC 2019: 16th International Conference, Held as Part of the Services Conference Federation, SCF 2019, San Diego, CA, USA, June 25-30, 2019, Proceedings 16 (pp. 107–114). Springer International Publishing. doi:https://doi.org/10.1007/978-3-030-23554-3_8

Richad, R., Vivensius, V., Sfenrianto, S., & Kaburuan, E. R. (2019). Analysis of factors influencing millennial's technology acceptance of chatbot in the banking industry in Indonesia. *International Journal of Civil Engineering and Technology, 10*(4), 1270–1281.

Ringle, C. M., Sarstedt, M., Schlittgen, R., & Taylor, C. R. (2013). PLS path modeling and evolutionary segmentation. *Journal of Business Research, 66*(9), 1318–1324. doi:https://doi.org/10.1016/j.jbusres.2012.02.031

Rogers, E. M. (1983). *Diffusion of innovations.* New York: Free Press.

Safeena, R., Date, H., Kammani, A., & Hundewale, N. (2012). Technology adoption and Indian consumers: Study on mobile banking. *International Journal of Computer Theory and Engineering, 4*(6), 1020–1024.

Salisu, Y., & Bakar, L. J. A. (2019). Technological capability, relational capability and firms' performance: The role of learning capability. *Revista de Gestão, 27*(1), 79–99. doi:https://doi.org/10.1108/REGE-03-2019-0040

Sarbabidya, S., & Saha, T. (2020). Role of chatbot in customer service: A study from the perspectives of the banking industry of Bangladesh. *International Review of Business Research Papers, 16*(1), 231–248.

Sayiwal, D. S., & Alankar, P. G. (2020). Chatbots in banking industry: A case study. *Journal of Emerging Technologies and Innovative Research, 7*(6), 1498–1502.

Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications, 9*(3), 209–216. doi:https://doi.org/10.1016/j.elerap.2009.07.005

Schwab, K. (2016). *The fourth industrial revolution.* New York: Cross Business.

Shankar, A., & Kumari, P. (2016). Factors affecting mobile banking adoption behavior in India. *Journal of Internet Banking and Commerce, 21*(1), 1–24.

Sidhu, M. K. (2018). The impact of internet banking on bank performance: Empirical evidence from Indian Banks. *Journal of Commerce and Accounting Research, 7*(2), 1–8.

Subrahmanyam, N., Bhayani, S., Rao, P. V., & Rajan, G. (2021). Digital aspects of banking progress and way forward with special reference to a rural areas in Andhra Pradesh. *Journal of Commerce and Accounting Research, 10*(3), 72–78.

Tarbal, J., (2020). *Chatbots in financial services: Benefits, use cases & Key features 2020.* Retrieved from https://www.artificial-solutions.com/blog/chatbots–financial–services–benefits–use–cases.

Tom, R., & Krishnan, R. M. (2021). A model of antecedents of behavioural intention to use online banking: Mediating role of perceived ease of use. *Journal of Commerce and Accounting Research, 10*(2), 30–39.

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), 91–111. doi:https://doi.org/10.1080/15332861.2019.1567188

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. Retrieved from https://www.jstor.org/stable/2634758

Wen, F., Xu, L., Ouyang, G., & Kou, G. (2019). Retail investor attention and stock price crash risk: Evidence from China. *International Review of Financial Analysis, 65*(2), 26–36. doi:https://doi.org/10.1016/j.irfa.2019.101376

Yiga, C., & Cha, K. J. (2016). Toward understanding the importance of trust in influencing Internet banking adoption in Uganda. *Information Development, 32*(3), 622–636. doi:https://doi.org/10.1177/0266666914563359