Factors predicting consumers' adoption of chatbots within the banking industry in South Africa

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ABSTRACT

Purpose: The aim of this study is to investigate the factors that make chatbots likely to be used in South African banking.

Design/methodology/approach: An online survey was used to obtain the primary data. The target population consisted of consumers who have a bank account and have experience with online banking in South Africa. A convenience and snowball sampling were used to recruit the required respondents. A total of 151 usable questionnaires were analysed using a quantitative approach and a structured questionnaire.

Findings: The empirical results show that perceived compatibility, perceived social influence, and perceived ease of use are predictors of chatbot adoption in the South African banking industry.

Research limitations/implications: Even though the study yielded significant findings, the small sample size of 151 respondents made it impossible to generalize the results. The survey was only available online, which could be a problem for people who do not know how to fill out surveys online.

Practical implications: The findings provide key stakeholders in the marketing and communications departments of the banking industry with in-depth knowledge of factors predicting the adoption of chatbots.

Social implications: The findings and implementation of the recommendations would enhance consumers' banking experiences.

Originality/value: Previous research in chatbots has not focused much on the banking industry in South Africa. In addition, there has been limited research with regards to AI use in the banking industry in Africa as well as in South Africa. This study helped to close these gaps. Theoretically, the findings contribute to the body of knowledge on digital marketing and thus assist the banking industry to enhance its online engagement using chatbots with the consumer.

Keywords: Perceived compatibility, social influence, perceived ease of use, chatbot adoption, banking industry, South Africa

INTRODUCTION

The marketing environment has experienced major transformation in the era of artificial intelligence (AI) particularly in the use of digital technology for marketing and advertising (Sima, Gheorghe, Subić & Nancu, 2020). South African banks are consistently exploring how they can use AI-powered chatbots to offer financial advice and help to customers. Furthermore, the banking sector in South Africa has undergone tremendous changes from providing paper-based banking services to adapting to modern digital technologies in the form of e-banking (Venter de Villiers et al 2020). Utilisation of technology that aims at offering meaningful experiences for the consumer and moving from in branch money transactions to online platforms has been the core of digital banking (Rahi, Ghani & Ngah, 2019). The use of artificial intelligence, the internet of things, and smart phones has largely caused a high demand for customer online interactions, especially within the banking sector (Rahi et al., 2019). The recent COVID-19 pandemic also made it clear how important it is to switch from traditional banking to digital banking.

The implementation of digital banking has been received with mixed reactions, with some consumers criticising or being reluctant to adapt to the changing ways of concluding transactions (Alalwan, Dwivedi, Rana & Algharabat, 2018). In the South African banking industry, chatbots are increasingly being adopted as a marketing tool (Eren, 2021). Chatbots can help customers make informed decisions based on their needs and preferences. For example, the Standard Bank of South Africa has implemented a chatbot, known as “AskSabi,” to assist customers with their banking activities, while First National Bank (FNB) has developed a chatbot called “AskFNB,” which can assist customers with various banking transactions, such as checking account balances and making payments.

The use of digital innovations by consumers (e.g., chatbots in the banking sector) is constantly changing because of changing consumer preferences and past experiences (Trustradius, 2020). Even though chatbots are characterised by several advantages for both the organisation and the consumer, it has been reported that the adoption rate has been very slow (Alalwan et al., 2018; Expert.ai Team 2020). Studies have reported that the adoption of chatbots in the banking sector has been impeded due to the perceived level of effectiveness, acceptance, and frequency of use of the application system (Khan, 2019; Rahi et al., 2019).

Besides the above challenges, most of the studies (Skafi, Yunis & Zekri 2020; Yin, Goh, Yang & Xiaobin 2021) on chatbots have been in the field of computer science rather than digital marketing (Eren, 2021; Rahi et al., 2019). The literature reviewed further shows a focus on chatbot implementation from a managerial perspective rather than consumer adoption, and a look at the South African banking industry context shows limited research focusing on digital marketing activities (Castri 2018 cited in Bhatti, 2019). Therefore, against this backdrop, results from previous studies such as that of Skafi et al (2020) and Yin et al. (2021) cannot be holistically transferable particularly to the South African digital marketing and the financial sector. Drawing from this background and gaps identified, it is imperative to identify the factors that predicts consumer adoption of chatbot within the banking industry in South Africa. Thus, the research question for this study is: “what are the factors that are predictors of chatbot adoption by consumers within the banking industry in South Africa?” The main objective of this study is to identify the predictors of chatbot adoption by consumers in the banking sector.

LITERATURE REVIEW

This section will present the literature on the use of chatbots within the South African banking industry. This will be followed by the main theoretical concepts underpinning this study.

THE USE OF CHATBOT IN THE SOUTH AFRICAN BANKING INDUSTRY

The banking industry in South Africa is composed of 36 licensed banks (Businesstech, 2020; Moyo, 2018). The size of banks in South Africa is normally determined by their assets, the services they offer, and their target market (Kapingura, 2013). However, one of the key challenges that the banking industry in South Africa is facing is the fast-paced digital technology evolution, which is affecting the industry as well as consumer engagement (PWC, 2021). The industry has embraced digital banking platforms, mobile banking applications, internet banking, and digital wallets to actively promote the use of digital banking (Fotso, 2020).

Chatbots have become a popular way in which the banking industry engages with its consumers. A chatbot is an artificial intelligence (AI) supported service tool that communicates with users over messaging apps, websites, mobile apps, or over the phone and analyses text from a consumer and links it to a database that contains possible answers (Baris, 2020; Crutzen, Peters, Portugal & Fisser, 2011). Chatbot permits immediate responses to questions posed by consumers without having to wait for a customer service representative to be available. Thus, a chatbot offers 24-hour omnipresent personal assistance aimed at solving consumer queries such as balance checks, sending money, and hyper-target marketing (Kaczorowska-Spychalska, 2019; Lubbe & Ngoma, 2021). Banks are now using AI-powered online chatbots to answer customer queries and process transactions to fit into the lifestyles of consumers without interrupting their convenience and comfort (Dapp, 2014; Mishra & Singh, 2015).

THEORETICAL PERSPECTIVE

The Technology Acceptance Model (TAM), the Diffusion of Innovation Theory (DoIT), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) formed the theoretical foundation of the study. The integration of these models in this study provides a comprehensive framework that will help to investigate the main predictors of consumer adoption of chatbots in the banking industry.

Davis (1989) proposed the Technology Acceptance Model (TAM), which consists of two components: perceived usefulness (PU) and perceived ease of use (PEOU). TAM is a renowned model used to judge the acceptance, use, and adoption of information technology (Goh & Wen, 2021; King & He, 2006). The model has been easily applied and validated in a wide range of new technologies and information systems, such as the adoption of electronic commerce (Pavlou, 2003), e-health systems (Wilson & Lankton, 2004), and mobile-based technologies (Almaiah et al., 2022; To & Trinh, 2021). For example, Almaiah et al, (2022) applied the TAM to investigate the most relevant factors that influence mobile learning readiness. Their study established that there is a positive and significant relationship between mobile learning readiness and awareness, IT infrastructure and top management support.

The DoIT, on the other hand, is a social and psychological theory aimed at assisting in the prediction of how people make decisions to adopt an innovation through investigating their adoption patterns and understanding its structure Rogers & Shoemaker (1983 cited in Min, So & Jeong, 2019). Innovation reflects an idea, object, or practice that is perceived by an individual, while diffusion is the process by which such innovation is communicated (Ali, Raza, Puah & Amin, 2019; Rogers, 2003). Skafi, Yunis, and Zekri, (2020) used the DoIT model in determining the factors influencing SMEs' adoption of cloud computing services in Lebanon. The results indicate that technological (complexity and security) and organisational (top management support and prior IT experience) factors are the main variables positively related to the decision to adopt cloud computing services (Skafi et al., 2020). DoIT is praised for its capacity to explain an innovation and its adoption or diffusion rate (Min et al., 2019).

Venkatesh et al. (2012) proposed the UTAUT2, which focuses on performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit as the key attributes impacting the behavioural intention of customers to accept and use technology (Sugumar & Chandra, 2021; Venkatesh et al., 2012). In an investigation of users' intentions to use m-wallets in Malaysia, Tang et al. (2014) employed the UTAUT2 model. The results from the study disclosed that performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, and habit have significant impacts on behavioural intention to use such a payment method (Rabaa'I, 2021). In the South African context, by extending the model to predict the acceptance levels of the people-to-people (P2P) services of the WeChat wallet in South Africa, the results showed that trust, security, and privacy together with TAM constructs are noteworthy in deducing the behaviour of South Africans to adopt the WeChat wallet (Rabaa'I, 2021).

PROPOSED INDEPENDENT VARIABLES FOR THE CURRENT STUDY

Considering the constructs in the TAM, DoIT, and UTAUT2 models, the following independent variables were proposed for the study.

Facilitating conditions

Facilitating conditions reflect the consumer's knowledge, ability, and resources available to use a chatbot online (Venkatesh et al., 2012). The absence of such facilitating conditions is likely to have a negative impact on technology usage and behavioural intentions (Al-Adwan et al., 2018). Based on a study by Toh and Tay (2022), facilitating conditions have been identified as one of the significant factors in explaining the acceptance of banking chatbots. Therefore, it is hypothesised that:

H1: Facilitation conditions significantly predict consumer adoption of chatbots in the South African banking industry.

Relative advantage

An innovation is likely to be adopted if it is perceived to offer more benefits than its predecessor (Ali et al., 2019; Al-Jabri & Sohail, 2012). Thus, relative advantage results in increased efficiency, economic benefits, and enhanced status associated with adopting an innovation (Al-Rahmi et al., 2021). Frambach and Schillewaert (2002); Sallehudin, Razak & Ismail, (2015); Al Ajam (2013) found significant correlations between relative advantage and adoption in their studies. Thus, it is hypothesised that:

H2: Relative advantage significantly predicts consumer adoption of chatbots in the South African banking industry.

Price value

Price value is the cost benefit attained for using an innovation such as chatbots (Dhiman et al 2019). The greater the price value, the higher would be the motivation to adopt the new technology (Dhiman et al., 2019). In other research studies such as on music streaming services (Helkkula, 2016), mobile learning adoption (Yang, 2013), TV streaming (Indrawati & Haryoto, 2015), instant messenger application (Indrawati & Marhaen, 2015), mobile banking (Mahfuz et al., 2016), it was confirmed that price value is a strong determinant of a consumer's behavioural intention. Based on previous research findings, it is hypothesised that:

H3: Price value significantly predicts consumer adoption of chatbot in the South African banking industry.

Hedonic motivation (HM)

Hedonic motivation (HM) is the joy, fun, playfulness, and entertainment of using a technology (Rabaa'I, 2021; Venkatesh et al., 2012). Previous research reveals HM to have a crucial role in accelerating users' intention to accept and adopt emerging systems in technology literature (Alalwan, Dwivedi & Rana, 2017; Rabaa'I, 2021; Toh & Tay, 2022). It is therefore hypothesised that:

H4: Hedonic motivation significantly predicts consumer adoption of chatbots in the South African banking industry.

Perceived Compatibility

Perceived compatibility is when an innovation fits into consumer banking needs, behaviour, values, experience, and practice (Al-Rahmi et al., 2021). In other words, compatibility occurs when the technology fits into consumer lifestyle. Kim and Galliers (2004) found that compatibility is positively related to an innovation's rate of adoption (Sanni et al 2013). Compatibility is a significant antecedent in determining consumers' attitude towards technology adoption in internet banking (Ndubisi & Sinti, 2006). Based on the preceding discussions, it is hypothesised that:

H5: Perceived compatibility significantly predicts consumer adoption of chatbots in the South African banking industry.

Social influence

Social influence is the extent to which a consumer feels it important to consider the input of significant others when deciding whether they should use the new system (Barre et al., 2021; Venkatesh et al., 2003). Moreover, information and reassurance given to the consumer by these people may play a key role in increasing consumer awareness of the technological processes (Alalwan, Dwivedi, Ran & Williams, 2016; Sugumar & Chandra, 2021). Social influence has emerged as a critical variable in the adoption and use of technological innovation such as online gaming, mobile applications, mobile payments, and service delivery (Barre et al., 2021; Sugumar & Chandra, 2021; Gursoy, Chi, Lu & Nunkoo, 2019). Therefore, it is hypothesised that:

H6: Social influence significantly predicts consumer adoption of chatbots in the South African banking industry.

Perceived ease of use

Perceived ease of use is when consumers feel like using self-service technology is easy and does not give them many problems (Davis, 1989). Lee, Hsieh and Hsu (2011) in their study on e-learning, observed a positive correlation between complexity and the perceived usefulness of e-learning. Previous studies have argued that when an innovation is perceived to be highly complex, users perceive it to be highly useful, even though they experience a certain degree of difficulty in using it (Al-Rahmi et al., 2021; Sanni et al., 2013). Therefore, it is hypothesised that:

H7: Perceived ease of use significantly predicts consumer adoption of chatbots in the South African banking industry.

Perceived usefulness

Davis (1989) describes perceived usefulness as the degree to which an individual trusts that using a particular device or system will improve his or her job performance (Pikkarainen et al., 2004). Past studies indicate that perceived usefulness is the strongest cognitive determinant of technology acceptance, as customers usually attach greater importance to whether they will benefit from using an innovation (Lubbe & Ngoma, 2021; Al-Emran, Arpaci & Salloum, 2020; Alshurideh, Al Kurdi, Salloum, Arpaci & Al-Emran, 2020). Therefore, it is hypothesised that:

H8: Perceived usefulness significantly predicts consumer adoption of chatbots in the South African banking industry.

DEPENDENT VARIABLE – CONSUMER ADOPTION OF CHATBOT

Consumer adoption of chatbot constitutes the dependent variable of the study. Technology adoption is a multi-phase process that starts with conceiving the idea to adopt an innovation (selecting, purchasing, or committing to use it) and then achieving regular use of a brand or a service (Nadal, Doherty & Sas, 2019). Rogers (2003) and Faisal and Idris (2020) argue that the social compact within which an individual exists and interacts in a community could motivate an individual to use a new technology. The social influence may involve the opinions of influential people in the society. Positive attitudes towards an innovation may influence its adoption by other consumers and the persistent use of such a technology.

RESEARCH METHODOLOGY

The study adopted the quantitative research method, which helped in applying statistical methods to test hypotheses in the study (Saunders, Lewis & Thornhill, 2012). The population for this research involved consumers of the banking industry's products and services in South Africa. The target respondents consisted of consumers who have used or experienced online banking activities in South Africa. Respondents were chosen from private and commercial banks. The exact population and sampling frame of consumers with knowledge of chatbots or who had used chatbots to access banking services in South Africa were unknown. However, based on the minimum sample size recommended by Survicate (2022), Hair et al. (2017), and Roscoe (1975), Javadi, Dolatabadi, Nourbakhsh, Poursaeedi and Asadollahi (2012), Chin and Newsted (1999 cited in Hur, Ahn, & Kim), a sample size of 200 respondents was chosen for this study. The respondents had to be 18 years of age or older and have an account with any of the South African registered banks. In addition, the respondents had to be consumers who had experienced online banking.

An online structured questionnaire was distributed through QuestionPro to collect the primary data. Convenience and snowball sampling method was used to recruit the target respondents. The link was shared through the researchers' email contacts and social media platforms with potential respondents. Only respondents who are available and had given consent to participate in the study were allowed to complete the questionnaire. The respondents were also encouraged to send the link to the survey to other potential respondents. Closed-ended questions and five-point Likert scales were used. Having standard questions promotes quicker interviews and makes analysis easier (Sommer & Gamper, 2021). All the questions were adapted from already validated measuring instruments in the literature or self-developed by the researcher (Al-Rahmi et al., 2021; Faisal & Idris 2020; Rabaa'i 2021; Venkatesh et al. 2012). The face validity of the measuring instrument was ensured by involving two subject experts in digital marketing and artificial intelligence in the design of the questionnaire. The gathered data was coded and captured on a Microsoft Excel spreadsheet. Thereafter, IBM SPSS version 16 was used to analyse the data. The data analysis includes descriptive and inferential statistical calculations.

The researcher obtained ethical clearance from the University Faculty Ethics Research Committee. The ethics clearance number for this study is H22-BES-MRK-097. The recruitment of respondents was voluntary, and respondents were assured of the confidentiality of information. Potential respondents were able to withdraw from participation if they felt uncomfortable. All participants indicated their consent to participate before being allowed to complete the questionnaire.

FINDINGS

A total of 352 questionnaires were received, of which 151 were usable and used in the data analysis. When compared with the proposed sample size of the study, this represents a response rate of 75.5%. Table 1 represents the profile of the sample. It emerged that slightly more than half of the respondents (56%) were female. Respondents between 36 and 45 years of age were mostly represented in the survey (42%). The sample is made up of predominantly (59%) full-time employed individuals, which could be a contributing factor to their having bank accounts. 33% of the respondents possess a postgraduate degree, followed by those who have a degree (30%) or diploma (25%). Only 1% of the respondents have a qualification below the matriculation certificate.

TABLE 1: PROFILE OF THE SAMPLE

Category	Frequency	Percentage (%)
Gender of respondents		
Male	60	40
Female	85	56
Other	6	4
Total	151	100
Age grouping		
18-25 years	14	9
26-35 years	43	29
36-45 years	64	42
46-55 years	25	17
56-65 years	5	3
Total	151	100
Employment status		
Full-time employment	89	59
Part-time employment	20	13
Retired	4	3
Student	29	19
Other	9	6
Total	151	100
Education level		
Below Matric level	2	1
Matric level certificate	10	7
Certificate	6	4
Diploma	38	25
Degree	45	30
Postgraduate degree	50	33
Total	151	100

Source: Results from primary data of the study

VALIDITY AND RELIABILITY TESTS

To find out how many factors were in the data set, an exploratory factor analysis was done. Using an eigenvalue greater than 1 and a scree plot, nine factors were identified from the items in the questionnaire. Furthermore, as recommended by Hair et al. (2006), factor loadings greater than or equal to 0.450 guided the study, as they were deemed significant at the =0.05 level for the sample size of 151. Cronbach's alpha coefficient was established to examine the reliability of the measuring items. According to Shrestha (2021), a Cronbach alpha coefficient value of 0.70 and above is deemed as reliable. The results of the reliability test are reported in Table 2. All the Cronbach alphas are greater than 0.80, which indicates excellent reliability and implies that the items measuring the various factors are reliable.

TABLE 2: CRONBACH'S ALPHA COEFFICIENTS FOR THE FACTORS

Variable	Cronbach's Alpha
Facilitating conditions	0.81
Relative advantage	0.86
Price value	0.86
Hedonic motivation	0.84
Perceived compatibility	0.87
Social influence	0.92
Perceived ease of use	0.88
Perceived usefulness	0.85
Chatbot adoption	0.88

Source: Results from primary data of the study

DESCRIPTIVE STATISTICS OF THE FACTORS

The mean score, standard deviation, minimum, quartile, median, and maximum values of the data are reported in Table 3. The mean score for all the factors ranged from M = 3.34 to M = 4.27. The highest mean score relates to relative advantage, while the lowest mean score is the social influence factor. All the standard deviation values are below SD=2.0, suggesting that they are closely knitted around the mean scores. Hence, there are no concerns about outliers. The minimum value is 1.00, and the maximum value is 5.0.

TABLE 3: CENTRAL TENDENCY AND DISPERSION

Factors	Mean	S.D.	Minimum	Quartile 1	Median	Quartile 3	Maximum
Facilitating conditions	4.07	0.59	1.00	3.71	4.14	4.43	5.00
Relative advantage	4.27	0.57	1.00	4.00	4.25	4.63	5.00
Price value	4.18	0.72	1.00	4.00	4.20	4.60	5.00
Hedonic motivation	3.83	0.74	1.00	3.40	4.00	4.40	5.00
Perceived compatibility	4.16	0.66	1.00	4.00	4.17	4.50	5.00
Social influence	3.34	1.01	1.00	2.67	3.50	4.09	5.00
Perceived ease of use	4.10	0.66	1.25	3.75	4.25	4.50	5.00
Perceived usefulness	4.23	0.60	1.00	4.00	4.29	4.64	5.00
Chatbot adoption	3.92	0.64	1.00	3.67	4.00	4.33	5.00

Source: Results from primary data of the study

RELATIONSHIPS BETWEEN THE FACTORS

The Pearson Product Moment Correlations were used to determine how the variables and chatbot adoption are related to each other. For this analysis, a correlation coefficient (r) is statistically significant if $|r| >= 0.160$ for $n = 151$ and practically significant if $|r| >= 0.300$ for any sample size. It is significant (both statistically and practically) if $|r| >=.300$ (Gravetter & Wallnau 2009). The results of Pearson's product moment correlations are presented in Table 4 below.

TABLE 4: PEARSON PRODUCT MOMENT CORRELATIONS

Factors	Perceived usefulness	Perceived ease of use	Facilitating conditions	Price value	Hedonic motivation	Social influence	Perceived compatibility	Relative advantage
Perceived usefulness	-							
Perceived ease of use	.543**	-						
Facilitating conditions	.662**	.652**	-					
Price value	.660**	.589**	.751**	-				
Hedonic motivation	.538**	.502**	.645**	.613**	-			
Social influence	.159	.171*	.300**	.152	.457**	-		
Perceived compatibility	.486**	.470**	.637**	.611**	.595**	.307**	-	
Relative advantage	.471**	.459**	.561**	.606**	.507**	.117	.720**	-
Chatbot adoption	.512**	.507**	.579**	.535**	.566**	.387**	.558**	.481**

Source: Results from primary data of the study

The results indicate that there is a practical and significant relationship between chatbot adoption and all the identified independent factors. The weakest relationship exists between social influence and chatbot adoption ($r = 0.387$). A moderate correlation but the biggest was established between facilitating conditions and chatbot adoption ($r = 0.579$). Furthermore, the relationship between social influence and perceived ease of use ($r = 0.171$) is practical but not statistically significant. Moreover, no practical and statistically significant relationship exists between social influence and the following factors: perceived usefulness ($r = 0.159$), price value ($r = 0.152$), and relative advantage ($r = 0.117$). The strongest correlation was found between price value and facilitating conditions ($r = 0.751$) and between relative advantage and perceived compatibility ($r = 0.720$). Although these relationships have been established, the focus of this study is to identify the predictors of chatbot adoption.

STEPWISE MULTIPLE LINEAR REGRESSION (SMLR)

A stepwise multiple linear regression analysis was done to find the factors that predict chatbot use in the banking industry and to test the study's hypotheses. In Table 5, it emerged that perceived compatibility ($p = 0.009$), social influence ($p = 0.017$), and perceived ease of use ($p = 0.022$) are factors that significantly predict the adoption of chatbots.

TABLE 5: SMLR RESULTS (N=151)

Independent variables	Coefficients	Std Err	t(144)	p-value	Hypotheses	Decision
Intercept	0.672	0.302	2.227	0.028**		
Facilitating conditions	0.179	0.110	1.693	0.093	H_1	Not supported
Relative Advantage	0.101	0.046	1.105	0.271	H_2	Not supported
Price Value	0.122	0.060	1.213	0.227	H_3	Not supported
Hedonic Motivation	0.137	0.080	1.765	0.080	H_4	Not supported
Perceived Compatibility	0.214	0.080	2.648	0.009**	H_5	Supported
Social Influence	0.106	0.044	2.424	0.017**	H_6	Supported
Perceived Ease of Use	0.184	0.079	2.320	0.022**	H_7	Supported
Perceived Usefulness	0.159	0.089	1.899	0.060	H_8	Not Supported

Notes:

[a]Dependent variable: Chatbot adoption

[b]Adjusted R^2= .449; F(5;145)=25.451; **p<0.0005; Std.Error of estimate=.4775

DISCUSSIONS, CONCLUSIONS, AND IMPLICATIONS

The goal of this study was to find out what factors make consumers of South African banks more likely to use chatbots. To reach this goal, nine factors (facilitating conditions, relative advantage, price value, hedonic motivation, perceived compatibility, social influence, perceived ease of use, perceived usefulness, and chatbot adoption) were found in the literature and used as the basis for the study. The exploratory factor analysis revealed nine factors, consisting of eight independent factors (facilitating conditions, relative advantage, price value, hedonic motivation, perceived compatibility, social influence, perceived ease of use, and perceived usefulness) and one dependent factor (chatbot adoption). The results revealed that perceived compatibility (p = 0.009) is a significant predictor of chatbot adoption. The mean score for perceived compatibility is 4.16. The results further indicate that there is a statistically and practically significant relationship between perceived compatibility and chatbot adoption. The findings imply that if a chatbot is compatible with all aspects of a consumer's lifestyle, customer service queries are handled urgently, and it fits well with consumer banking needs, then it is likely that consumers will adopt chatbot use. Therefore, the more compatible or well-matched an innovation is with a consumer's knowledge, the higher the chatbot adoption rate. Consequently, perceived compatibility is an important factor for consumers when making decisions about chatbot adoption. The results of the current study are consistent with prior studies that found that perceived compatibility motivates consumers' attitudes towards the adoption of new technology (Kim & Galliers, 2004; Sanni et al., 2013; Ndubisi & Sinti, 2006). The results suggest that it is important to develop and implement banking chatbots in a way that is compatible with the lifestyle and values of the bank's customers. Therefore, the hypothesis (H5) formulated for the study is supported.

Based on the correlation analysis, there is a link between social influence and the use of chatbots. The significant relationship is, however, weak. The mean score of M=3.34 was recorded for the social influence factor. Based on the results in Table 5, social influence (p = 0.017) was identified as a factor that significantly predicts chatbot adoption in the South African banking industry. This implies that even though the variable is significant, consumers consider it very important in their behaviour towards chatbot adoption. Considering chatbot adoption in the banking industry, consumers are likely to perceive the recommendation by influential people as their priority to adopt chatbots. In prior studies, the social influence has proved to be important in explaining the usage of technological innovation (Barre et al., 2021; Sugumar & Chandra, 2021; Gursoy, Chi, Lu & Nunkoo, 2019). Thus, hypothesis (H6) formulated for the study is supported.

Perceived ease of use was also identified as a factor that predicts chatbot adoption in the banking industry ($p = 0.022$). Perceived ease of use attracted a mean score of 4.10 and revealed that there is a significant correlation with the adoption of chatbots within the banking industry. The variable is influenced by factors such as improved transacting online, which is easy to navigate, reduces human error, and offers a mentally and physically effortless experience. In accessing banking services, consumers' main concern is having their needs met in an easy way. Hence, in designing a chatbot, banks should prioritize the ease of using the application. The findings are consistent with previous research, which found that consumers would adopt an innovation based on its perceived ease of use (Al-Rahmi et al., 2021; Sanni et al., 2013; Lee, et al., 2011). Therefore, hypothesis (H7) is supported.

The study's results showed that even though factors such as facilitating conditions, relative advantage, price value, hedonic motivation, and perceived usefulness were linked to chatbot adoption, they did not predict chatbot adoption in the banking industry. Thus, the following hypotheses (H1, H2, H3, H4, and H8) are not supported.

RECOMMENDATIONS, LIMITATIONS, AND FUTURE RESEARCH AREAS

The main goal of this study was to investigate what makes South African banking customers more likely to use chatbots. The empirical results showed that perceived compatibility, perceived social influence, and perceived ease of use are all strong predictors of chatbot adoption by South African banking customers. Based on the findings, the following recommendations are made: banks should strive to ensure that their chatbot technology and applications are compatible with all smart devices and gadget types and not limited to just a few. Banks should develop chatbot innovations and applications that are compatible with the lifestyles of consumers in South Africa.

This study established that consumers' decisions to adopt chatbots for accessing banking services are predicted by how easy the system is to use and does not require too much effort to learn and use. It is recommended that banks design chatbot applications that are not complicated to use. The marketing department of the banks should create a chatbot awareness campaign to expose and educate potential consumers on the benefits of and how to use chatbots. The marketing department in the banking sector in South Africa should also develop a unique marketing concept that could be used to convince consumers to adopt chatbots. Banks should also make use of social influences, particularly those of ordinary citizens, to convince consumers to adopt chatbots. This might enhance the social influence within the society.

This study contributes to the literature on consumer adoption of chatbots in the banking industry in South Africa. The study also identified the factors that industry practitioners within the banking industry could priotise to enhance the use of Chatbots and remain sustainable in future disruptions. However, the following limitations should not be overlooked. Firstly, only 151 usable responses were used in the data analysis. In addition, the survey was conducted online, which was a disadvantage to those who were not well versed in how to navigate an online survey. The study also did not narrow down to a particular banking chatbot system but examined chatbots in the banking industry in general; therefore, future research can consider a particular chatbot application. In the future, the study's identified factors can be replicated in a different geographic location (country). A conscious effort should be made in the future to increase the sample size in an effort to generalize the findings.

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