International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2024, 14(1), 73-84.

Modelling Factors Influencing Bank Customers' Readiness for Artificial Intelligent Banking Products

L. Garekwe, S. J. Ferreira-Schenk, Zandri Dickason-Koekemoer*

Faculty of Economic and Management Sciences, North-West University, South Africa. *Email: 20800274@nwu.ac.za

Received: 09 September 2023 **Accepted:** 10 December 2023 **DOI:** https://doi.org/10.32479/ijefi.15238

ABSTRACT

In the era of globalisation and technological development, artificial intelligence (AI) plays a significant role in financial activities and services. AI in financial technology has a clear potential to accelerate the financial industry's transformation by offering excellent value to customers by providing tailor-made products and services, thus improving customer experience. The paper aims to model the factors influencing bank customers' readiness for artificially intelligent banking products within the South African banking sector. Data were collected from 346 banking customers within South Africa. The study results revealed that demographic and socio-cultural variables influence the readiness for artificially intelligent banking products. Behavioural finance biases also influence bank customers' readiness for artificially intelligent banking products. Furthermore, the study also found that customers' readiness for artificial intelligent banking products is faced with the limitation of the inaccessibility to technological tools in rural areas. Consequently, policies that can improve infrastructure and enable rural citizens to cope with advanced technology can improve bank customers' readiness for artificially intelligent banking products in South Africa.

Keywords: Artificial Intelligence, Banking Sector, Customers' Readiness, South Africa
JEL Classifications: E58, G21, G24

1. INTRODUCTION

The evolution of banks as institutions of organising and protecting customers' financial interests have pioneered the involvement of financial technology to drive business value (Jubraj et al., 2018). Financial technology, commonly known as FinTech, refers to technologically enabled financial solutions. According to Arner et al. (2016), it is now widely regarded as the new union of financial services and information technology. However, the relationship between finance and technology has a long history. Masocha et al. (2011) state that it has been a standard feature of the banking industry for the past three decades, but its use was first confined to the automation of back-office processes. However, the widespread adoption of technology in customer-facing roles has seriously challenged this notion. Accordingly, Nasri (2011) asserts that technology has become a fundamental driver in the radical change of banking, breaking geographical, legal, and economic boundaries and creating new products and services. As the market modernises, traditional banking models cannot meet the increasing customer needs and decisions (Khan et al., 2017). This is because of the pervasiveness of information on the internet. Customers are better aware of and, as a result, more demanding of personalised banking solutions (Coetzee, 2018a). Therefore, over the next decade, banks will have to fundamentally alter how they conduct business as customer preferences and technological advancements affect their services, products, and interactions. Giovanis and Athanasopoulou (2018) state that traditional bank branches with standard automated devices and banking employees cannot satisfy customer needs for intelligent banking services to fit their rapid lives in many areas globally.

However, Park et al. (2016) claim that AI in financial technology has a clear potential to accelerate the financial industry's transformation by offering excellent value to customers by providing tailor-made products and services, thus improving customer experience. The rapid evolution of FinTech is a driving force behind today's AI-driven digital age. Biometrics, virtual assistants, and humanoid robots are all examples of AI technologies that, when applied after risks have been mitigated, may often outperform human decision-making in terms of speed and accuracy. AI is a subfield of computer engineering that articulates the development of intelligent machines that function and interact similarly to humankind (Kurzweil et al., 1990). However, according to Paschen et al. (2019), AI differs from human intellect since it is based on fast data processing. The intelligence in AI can be seen as the capacity to analyse and turn data into information that guides action. Poole and Mackworth (2010) add that AI computational agents are created to mimic human strength while outperforming it in precision. Significant benefits for banks and a possible boost in customer satisfaction could result from strategically using AI technologies at critical customer touchpoints. Therefore, banks are rapidly adopting AI technologies backed by data analytics to improve customer expectations (Biswas et al., 2020).

Owing to the aforementioned improvement in the banking sector, banks are entering a more competitive technological intelligence age. This competition forces them to redefine their daily processes, create innovative products, and ultimately transform customer experiences (Jubraj et al., 2015). However, customers may have varying perceptions of the services that AI technology in fintech may offer; while customers' satisfaction with banks' efficiency may be seen as a more imperative service (Redda 2015). According to Roy and Moorthi (2017), banks also had to work on customer perception of trust and how it seems to maintain bank-customer relationships. Furthermore, one challenging impediment to implementing such technologies in Africa and South Africa, particularly, are socioeconomic challenges and interaction preference (Coetzee, 2018a). Most South Africans struggle with socioeconomic issues such as inequality, unemployment, and poverty. At the same time, most individuals reside in outlying regions lacking traditional banking services (Coetzee, 2009). Since these customers are typically less well-educated and more reliant on dealing with human interaction, technological products can be a problem in adopting AI banking products (Hesse, 2018).

2. LITERATURE REVIEW

2.1. An Overview of Technological Adoption Models

Several model theories, such as the Theory of Planned Behaviour (TPB), the Theory of Reasoned Action (TRA), and the Technology Acceptance Model (TAM), has been developed to analyse and comprehend the factors that impact the adoption of new technologies (Thowfeek and Mirzan, 2017). The TAM model was derived from Ajzen and Fishbein's (1975) TRA model, a theory of reasoned action based on the concept that a person's response and perception of something determines that person's attitude and behaviour. Although Payne et al. (2018) viewed TAM as a viable instrument for exploring and researching the adoption of Internet banking, mobile banking, and cardless banking, the model could not capture the dimension of trust and risk related to technological adoption behaviours. As a result, the model's predictive capacity for adoption behaviour is severely constrained. To address this limitation, several researchers, including Masinge (2010); Nasri (2011); Mamina and Maziriri (2020), and Sitienei (2020), expanded the TAM model to incorporate additional factors that might influence the adoption of new technology in banking. Thus, researchers value user intentions toward new adoption because they enable financial organisations such as banks to get actual value from knowing the critical aspects that impact the intention to use technology in the digital age (Mohammadi, 2015).

2.2. Review of Factors Influencing the Adoption of Technology

Nasri (2011) asserts that technology has become a fundamental driver in the radical change of banking, which has resulted in breaking geographical, legal, and economic boundaries and creating new products and services. As the market modernises, traditional banking models cannot meet the increasing customer needs and decisions (Khan et al., 2017). In this regard, Giovanis and Athanasopoulou (2018) state that traditional bank branches with standard automated devices and banking employees cannot satisfy customer needs for intelligent banking services to fit their rapid lives in many areas. Demographics, technology readiness, convenience, safety/security, and trust/reliability are factors known to influence the adoption of technology in banking.

2.2.1. Demographical and socio-cultural factors used in the adoption of AI

When analysing the factors that influence customers to adopt new technology, it is imperative to consider certain demographical and socio-cultural factors that may help the effect of the adoption process (Belanche et al., 2019). These elements include age, gender, ethnicity, income level, educational attainment and banking knowledge.

According to Nasri (2011), age has been linked to various banking technology acceptance. Research by Achieng and Ingari (2015) has revealed that older individuals have more fixed views and are less sensitive to others' opinions than younger people. Ngai et al. (2007) research also represented such sentiments, which found that younger customers are more inclined to adopt online banking since they are more comfortable with the internet. Furthermore, Sleiman et al. (2021) agree with Ngai et al. (2007) that such trends exist because younger customers are less concerned than their older counterparts about the absence of face-to-face interaction inherent in online banking systems. This idea is also corroborated by Laumer et al. (2010), who claimed that elderly customers have unfavourable opinions about internet banking because they cannot understand its benefits.

When researching technological adoption, it is also essential not to overlook the importance of gender (Marangunić and Granić, 2015). Gender is a well-recognised and researched factor in information and social science studies. According to Chung (2014), past research has shown significant variations between men and females regarding embracing and using technological devices. Such to the findings of Biswas et al. (2020), female bank customers are less inclined to do their banking operations online. In addition, regarding the behavioural intention to use mobile payment, Nasri (2011) discovered that females value perceived convenience. Therefore, females favour convenience items or services while doing online activities.

On the other hand, males are more influenced by performance and effort expectations (Sleiman et al., 2021; Al-Azawei, 2019; Venkatesh et al., 2003) and share the same sentiments that gender is essential in adapting to technology. Their studies indicated that women are more concerned with ease of use, while men are more concerned about the usefulness of technology.

Despite the rising use of technology in daily life areas such as healthcare, education and banking activities, the use of technology continues to be impeded by ethnic obstacles. Jackson et al. (2008) claimed that ethnicity might represent access to technology and cultural influence. Multicultural societies are defined by several social groups, notably ethnic and racial minorities, who occupy various places in the social stratification structure (Chen, 2013), according to Akhtar et al. (2019), ethnicity is cultural programming that distinguishes one kind of people from another. However, culture, in particular, is not a trait of a single individual; instead, it is an element of collective people who have combined their resources to form a community, which may eventually serve as a model for human conduct and influence one's way of life (Robinson et al., 2015). From a global perspective, digital inequalities often exacerbate racial and ethnic disadvantages due to the economic divide between Western and African countries (Robinson et al., 2015). According to Ono and Zavodny (2007), numerous studies have shown a racial digital gap in information technology usage. According to Dupagne and Salwen (2005), there are significant disparities in communication technology adoption between Whites, Africans, and Hispanics, even after adjusting for socio-economic characteristics. According to Kim et al. (2014), Caucasians are more likely than non-Caucasians to use technology. Further, according to Jackson et al. (2008), African people continue to use the internet less intensively than adults from other ethnic groups, even when access is not a concern and characteristics associated with internet usage, such as income and education, are controlled.

In adopting technology, Van Deursen et al. (2011) state that educational attainment is also essential to consider. Because this variable is also a function of ethnicity, empirical data imply that education is positively associated with technology adoption (Marakarkandy et al., 2017). High levels of technology ownership define better-educated classes of people, the availability of internet connection at home, high levels of broadband connectivity, and the fact that they spend much more time online than the general population (Buente and Robbin, 2008). Additionally, according to Lopez et al. (2013), less-educated populations cannot relate the information the Internet offers to their functional requirements. An additional argument advanced by Yuan et al. (2016) is that educated bank customers can better keep up with technological improvements and have a competitive advantage over those who do not. Ramavhona and Mokwena (2016) similarly agree with Buente and Robbin (2008) that affluent and highly educated groups are more receptive to change, making them the most likely class of customers to embrace digital banking.

2.2.2. Technology readiness

According to Van Dyk and Van Belle (2019), technology has accelerated transformation in fields such as banking. This trend is expected to continue as present technologies improve speed, capacity, usefulness, and simplicity. However, as Parasuraman and Colby (2015) point out, customers are confronted with different trade-offs when maximising the benefit of technology-based service alternatives while avoiding dissatisfaction or failure. As a result, the value and practical significance of the Technology Readiness (TR) construct will continue to develop in sync with the fast evolution of technology. According to Musyaffi et al. (2021), the idea of technological readiness is described by Parasuraman (2000) as a customer's inclination to adopt and apply new technologies in transaction performance. Rekarti and Hertina (2014) describe technology readiness as a psychological state in which individuals are willing to accept new technology. Thus, TR derives from the notion that it is difficult for individuals to adapt to new situations (Roy and Moorthi, 2017). Kim et al. (2014) indicate that technology is seen as a step forward for optimistic and inventive groups. However, technology is viewed as a step back for sceptical groups until the group has adequate confidence. Parasuraman and Colby (2015) defined five customer types based on their technology readiness level. The five customer types are detractors, pioneers, sceptics, paranoids, and explorers, with the explorers being the most technologically prepared and the detractors being the least prepared (Gupta and Garg, 2015). Several studies, including Parasuraman (2000); Zolait et al. (2009); Gupta and Garg (2015); and Musyaffi et al. (2021), have established that technological readiness influences Fintech adoption in the banking sector. However, Berndt et al. (2010) note that although South Africa is a developing country and offers opportunities for expansion in financial services, there are impediments associated with customers being prepared to utilise new technology. Low levels of financial literacy and science and math skills raise doubts about the widespread adoption of technology in rural areas and instead show a preference for face-to-face interactions at physical branches.

2.2.3. Convenience

According to Kazi (2013), the early definitions of convenience were established by Yale and Venkatesh (1986) as a class of customer products that are widely available and need minimum time and physical and mental effort to acquire. Nasri (2011) further mentions that convenience emphasises resources such as the effort and time required by the user to complete an activity. From a Self-Service Technology (SST) perspective, the perceived convenience of SST, according to Kim et al. (2014), is the customers' opinion that using the SST would allow them to finish the activity quickly and at a time and location of their choice. For instance, customers' efforts to bank utilise technologies such as online banking rather than traditional banking. Several researchers, including Liao and Cheung (2002) and Hoo et al. (2021) mention that banking technology such as internet banking provides convenience. Customers may bank online to pay bills, check balances, transfer funds, apply for loans and mortgages, and utilise other supplementary services from any location at the touch of a finger. Consequently, customers tend to value the ability to save time and have access to their accounts. Saving time and providing customers with 24/7 access appear to be internet banking services' (Chakiso, 2019). Studies including Liao and Cheung (2002); Chakiso (2019); and Hoo et al. (2021) have discovered a positive correlation between convenience and acceptance of new technologies. However, Shaw and Sergueeva (2016) emphasise that convenience is a construct in and of itself and caution against conflating it with perceived ease of use. For example, using an Apple wallet to pay at a physical store may be convenient since the digital wallet can store several payment cards and allow various payment options. However, depending on how the application is designed, it may or may not be easy to use. The inclusion of convenience in the research is motivated by the need to understand better how convenience influences the adoption of technology by banking customers.

2.2.4. Safety and security

It is becoming increasingly common for customers to be concerned about security and privacy when using banking technology (Kumar and Balaramachandran, 2018). However, AI has evolved into a powerful tool for identifying and preventing cybercrime (Dilek, 2015). Aside from that, institutions in South Africa are compelled to comply with all applicable legal requirements to secure customer information under the Protection of Personal Information (POPI) Act (Van Dyk and Van Belle, 2019). In contrast, a frequent and well-acknowledged impediment to adopting e-commerce has been the absence of perceived security of new technology, which reveals risk as an extra dimension in adopting new technology (Hesamzadeh, 2021). Nonetheless, the failure of a banking server, cybercrimes, and the compromise of financial information would diminish customers' desire to adopt new banking technologies (Achieng and Ingari, 2015).

2.2.5. Trust and Reliability

With the rise of digitalisation, the financial services business has become more competitive. As a result, an emphasis has been placed on trust and reliability to develop stable, long-lasting relationships with clients (Coetzee, 2018b). Trust/reliability is a subjective perception that an organisation will inspire confidence in introducing new technology. Users are more sensitive to uncertainty risks and losing control (Slade et al., 2015). Ramli et al. (2021) state trust is based on truthful information, beliefs, or confidence. According to Slade et al. (2015) and Payne et al. (2018), trust was shown to be an essential predictor of behavioural intention. As a result, customers who perceive a high degree of trust are expected to adopt new technologies more. However, A complex and multidimensional construct, perceived trust, is particularly significant in uncertain and risky environments when it is most difficult to establish trust (Hakeem and Ratnasari, 2021). According to Lu et al. (2011), while trust and perceived risk have been shown to influence behavioural intention to use new technology positively, trust also has a significant association with the quality of service to satisfy customers.

2.2.6. Customer service quality

Namahoot and Laohavichien (2015) concur that trust is positively associated with perceived service quality. However, Pakurár et al. (2019) argue that service is ambiguous and complex because of heterogeneity, intangibility, perishability and consumption characteristics. More importantly, the fact that service definitions vary between customers. Nonetheless, Payne et al. (2018) state that to determine service quality, one must first comprehend the "need for service." As a result, Yussaivi et al. (2021) define the need for service as a customer's perceived requirement to engage with a service provider along the customer's route to a successful transaction. Furthermore, it is essential to differentiate between traditional and electronic services (e-services) (Sathiyavany and Shivany, 2018). According to Redda (2015), traditional service refers to the level of service given by human contact personnel rather than automated technologies. According to Worku et al. (2016), customer satisfaction with traditional services depends on face-to-face contact between the customer and the organisation.

In contrast, Alhkami and Alarussi (2016) describe e-services as the customer's overall evaluation and judgment of the service quality supplied through Self-Service Technology (SST). Sathiyavany and Shivany (2018) note that electronic services may be highly tailored based on data from numerous sources, and service delivery is not constrained by operation hours, but services are private. Lee (2017) states that the research indicates that the demand for physical interaction differs between customers of SST and non-customers. Pakurár et al. (2019) add that customers who have a greater desire for interaction with service professionals are not intuitively driven to adopt SST, such as humanoids. Similarly, customers may be reluctant to adopt AI services if they perceive greater service through contact with bank staff (Sathiyavany and Shivany, 2018). Regarding customer service, Aisyah (2018) defines service quality as the customer's evaluation of their encounters with SSTs or bank staff. Coetzee et al. (2013) assert that the digital environment varies from the traditional environment in the following ways:

- Absence of face-to-face engagement - clients in the digital environment communicate with their bankers through a technological interface rather than face-to-face conversation.
- Convenience and efficiency - when performing transactions, digital users benefit from the comfort of saving time and effort.
- Safety and confidentiality- users' privacy, security, and secrecy are all concerns of online engagement.

Coetzee et al. (2013) recognised the difficulty of evaluating service quality as a consequence of it being an "abstract and elusive concept" that is more difficult to assess than products due to the absence of "tangible cues" that enable assessment. In an attempt to measure the quality of service, the SERVQUAL measurement instrument was developed. SERVQUAL is a service quality measurement instrument that analyses customer expectations and perceptions (often referred to as the "disconfirmation technique"), and it has grown to be the most generally used instrument for evaluating service quality across a range of sectors (Alhkami and Alarussi, 2016).

2.2.7. Behavioural finance biases

Fakhry (2016) states that the financial decision-making environment is complex and uncertain. However, when faced with complexity, humans analyse information through cognitive and emotional processes, generating heuristics that simplify decision-making (Jain et al., 2015). While decision theory refers to the capacity of consciousness to make decisions, it can also be technically defined as selecting one option from multiple alternatives (Takemura, 2014). In this regard, Hyland et al. (2021) assert that behavioural finance focuses on the impact of human irrationality on financial decisions. Behavioural finance theories also explain individuals whose actions do not maximise expected utility (Pompian and Wood, 2006). Rossini and Maree (2010) assert that behavioural finance explores the influence of human psychology and emotions on financial decision-making. While traditional finance theories focus on how individuals act to maximise their wealth, behavioural finance theories examine how customers conduct themselves in an economic setting (Kourtidis et al., 2011). Various decision-making biases have been documented by psychological research. These biases can manifest in numerous facets of decision-making. Emotional and cognitive biases categorise behavioural biases (Hyland et al., 2021).

3. METHODOLOGY

Positivist researchers believe that knowledge received through direct observation is more realistic, trustworthy, and factual (Hammersley, 2012) To have a reliable perspective on the phenomena in question, the researcher adopted a positivistic research paradigm and assessed responses to questionnaires they distributed to participants (Pham, 2018). Participants in this study completed an online questionnaire as part of the methodology for quantitative research. This study's participants were banking customers with one or more banks in the South African bankhing industry. The sampling frame research consisted of South African retail, private and wealth banking customers where no personal information was required from customers.

3.1. Research Instrument and Sample Selection

Due to the Covid-19 regulations under the Disaster Management Act (57 of 2002), regulating that there should be fewer physical interactions. The collection of responses from participants was not done physically but electronically. A structured online questionnaire tool (QuestionPro) was used to construct the online questionnaire and gather the data. A hyperlink to the survey was disseminated by snowball sampling to 15 initial respondents through Twitter, Facebook, LinkedIn and WhatsApp. Respondent Anonymity Assurance was enabled in Questionpro, where specific fields were hidden (such as the respondent's email, IP address, country code and region) to protect the participants. This study was implemented on a sample size of 346 South African banking customers who contributed to the study. The sample size selection was based on previous studies in the banking sector and met the statistical requirement for the analysis to be employed. Non-probability convenience and snowball sampling were used to gather the data using a questionnaire. According to Bhardwaj (2019), non-probability convenience sampling is where the researcher selects easily accessible or available participants. Non-probability snowball sampling, also called "chain referral" sampling, is collected in various stages (Quinlan, 2011). First, the initial respondents to the questionnaire distributed the questionnaire further to other qualifying participants. The sample only included individuals 18 years and older with valid bank accounts with any South African banks. Pallant (2013) recommends at least a sample size of 150 participants with a ratio of five items for each variable for successful factor analysis. Therefore, this research examined a sample size of 346 South African banking customers, considering complete responses rate, expenses, and time restrictions.

3.2. Hypothesis

To test the empirical objectives of the study, the null hypothesis and alternative hypothesis were formulated as stated below:

H_{01}: *There is no significant relationship between demographics and technological readiness.*

H_{02}: *There is no significant relationship between behavioural biases factors and technological readiness.*

H_{03}: *There is no significant relationship between customer service quality factors and technological readiness.*

H_{04}: *There is no significant relationship between customer preference for traditional or digital banking factors and technological readiness.*

3.3. Statistical Analysis

The empirical objective of this study is to model factors influencing bank customers' readiness for artificially intelligent banking products. The authors developed a structural equation model (SEM) of the factors influencing bank customers' readiness for AI banking products to achieve this objective. The SEM is based on hypothetical relationships between multiple variables or constructs. One of the benefits of SEM is that it integrates statistical methodologies such as multivariate statistics to construct a single integrated model (Fan, 2007). These methods include confirmatory and exploratory factor analyses, correlation and covariance analyses, and multiple regression analyses (Hardy and Bryman, 2004).

4. EMPIRICAL RESULTS AND DISCUSSION

The sections below discuss the descriptive analysis of demographic variables and the structural equation model of the factors influencing customers' adoption of AI banking products in South Africa.

4.1. Descriptive Analysis and Comparison

Table 1 below indicates the demographic variables, such as age, gender, educational attainment, annual income and level of banking knowledge.

Participants were requested to identify their ages in five categories: 18-29 years, 30-39 years, 40-49 years, 50-59 years and 60 and above to participate in the study. However, as indicated in Table 1, the older age groups (40-49, 50-59, and 60 years above) were merged to create the 40 years and older group due to the data being negatively skewed (where the first two age groups had a higher proportion of respondents). It is also evident in Table 1, where the first age group, 18-29 years, accounted for the majority (43.1%) of the sample, representing 149 of the 346 customers. The second age group, 30-39 years, accounted for 37.3% of the sample, representing 129 of the 346 customers. The last age group, 40 years and older, comprised the least proportion of the sample (19.7%), representing 68 of the 346 customers. As per Table 1, 50.9% of the participants were male bank account holders, representing 176 of the 346 customers. In comparison, 49.1%

Table 1: Demographics and socio-cultural attributes

Demographic variable	Category	Frequency	Percentage
Age	18-29 years	149	43.1
	30-39 years	129	37.3
	40+years	68	19.7
Gender	Male	176	50.9
	Female	170	49.1
Ethnicity	African	289	83.5
	White	40	11.6
	Other	17	4.9
Education attainment	High school education	25	7.2
	Further training/3-year certification	37	10.7
	Undergraduate degree	102	29.5
	Honours degree	103	29.8
	Higher degrees	75	21.7
	Other	4	1.2
Annual income	Below R100 000	77	22.3
	R100 001—R200 000	29	8.4
	R200 001—R400 000	78	22.5
	R400 001—R550 000	53	15.3
	R550 001—R700 000	44	12.7
	R700 001—R1500 000	53	15.3
	R1 500 001 and above	12	3.5
Level of banking knowledge	Little	31	9.0
	Average	142	41.0
	Above–average	122	35.3
	Superior	51	14.7

of the sample was female bank account holders, representing 170 of the 346 customers. For this survey, participants had five options for identifying their ethnicity: African, Asian, Coloured, White, or other. However, the Coloured, Asian and Other were merged to create one group named other ethnicity. This is because of the negatively skewed data where the latter groups had small responses. Therefore, there were more African customers (83.5%) than any other race, as indicated in Table 1, followed by White (11.6%) and then Other ethnicities (4.9%). This translates to out of the 346 customers, 289 were African, 40 were White, and 17 were Other. Participants from other ethnicities made up the smallest minority of the sample, with only 1 out of 346 individuals. Participants were requested to categorise their educational attainment into eight categories: high school education, further training, 3-year diploma, undergraduate degree, honours degree, master's degree, doctoral degree, or other. However, the further training and 3-year diploma were merged to create one group named further training/3-year certification. Furthermore, the post-honours degrees (master's and doctoral degrees) were combined to form a higher degree group. According to the results shown in Table 1, of the total of 346 banking customers. Most customers reported honours degrees (29.8%) and undergraduate degrees (29.5%), with 103 and 102 customers in each group. Following that, 21.7% of the sample (75 customers) have a higher degree, 10.7% of the sample (37 customers) holds a further training/three-year diploma, and 7.2% of the sample (25 customers) hold a high school education. Other types of formal education are represented by a minority of the sample (1.2%), represented by four customers. Additionally, participants were requested to specify their annual earnings in one of seven interval groups ranging from <R100,000 to more than R1.5 million. Accordingly, customers were not explicitly asked to indicate their annual earnings. From Table 1, only 77 of the 346 customers, or 22.3% of the sample, earn <R100,000 each year. Contrary, a minority of 12 customers out of 346 (3.5% of the sample) earn more than R1.5 million each year. The majority (22.5%) of the sample earns between R200 000 and R400 000/year, accounting for 78 of the 346 customers. Additionally, as demonstrated in Table 1, the income categories R400 001 - R550 000 and R700 001-R1500 000 each account for 15.3% of the sample, or 53 individual customers. Accordingly, 12.7% of the sample earns between R550 000 and R700 000 per year. It is followed by 8.4% of the sample earning between R100 000 and R200 000 yearly. Finally, customers were asked to categorise their banking knowledge into four categories: little, average, above average, and superior. According to Table 1, 142 of the 346 customers reported having an average banking knowledge level, reflecting the majority of the sample (41.0%). In addition, 35.3% of the customers had above-average banking knowledge, while 14.7% reported having superior financial and banking knowledge. Finally, only 31 of the 346 customers reported little knowledge of banking matters, accounting for 9.0% of the sample.

4.2. Structural Equation Model

One of the benefits of SEM is that it integrates statistical methodologies such as multivariate statistics to construct a single integrated model (Fan, 2007). The first process in SEM is to identify variables or constructs based on theory as discussed in the literature review, define how they will be assessed, and characterise the interrelations between the different variables. The second process is to evaluate the structural model validity. Among these methods are confirmatory and exploratory factor analyses, correlation and covariance analyses, and multiple regression analyses (Hardy and Bryman, 2004).

4.2.1. Assess structural model validity

Kline (2014) emphasises the importance of assessing the model's validity and the hypothesised relationship of the multiple variables. Accordingly, the following goodness of fit indices is used to measure how well the hypothesised model fits the underlying data as part of the model assessment process.

- According to Malhotra et al. (2017), CFI values closer to 1 suggest a good fit. The model produced a CFI index of 0.673.
- A CMIN/DF (chi-square test statistics divided by the degrees of freedom) value of 2.18 indicated a good fit. Schumacker and Lomax (2004) necessitate lower values (preferably <5) because these measurements quantify error or deviation, and Plucker (2003) states that the standard for good fit entails values between 2 and 5.
- According to Malhotra et al. (2017), the RMSEA values of 0.08 or less suggest a strong model fit. Therefore, an RMSEA value of 0.06, with a 90% confidence interval of [0.058; 0.062], was obtained and indicated a good model fit.

The CMIN/DF and RMSEA values indicated a strong model fit, despite the CFI value being below the optimal value of more than 0.9. Consequently, the specified structural model fits the data well. In addition, there is sufficient evidence of construct validity. Hence the specified structural model is considered valid.

At a significance level of P = 0.05, Table 2 demonstrates that demographic factors, including age, ethnicity, income level, and the social-cultural factor level of banking, contributed to adopting AI banking products. However, as shown in Table 2, gender and educational attainment did not influence the adoption of AI products in banking. Regarding behavioural biases, it can be observed that only representativeness contributed (P = 0.07) to the adoption of AI banking products at a significance level of 5%. Interestingly, none of the customer service quality characteristics at the various significant levels (0.001, 0.05 and 0.1) contributed to the adoption of AI. However, Coetzee et al. (2013) claimed that service quality criteria such as assurance, reliability, responsiveness and tangibles are critical contributors to the perception of technology in South African retail banking. Concerning digital banking factors, Table 2 reveals that access to technology, convenience, safety, and security contributed to the contribution of technology at a significance level of $P < 0.001$ and that access to technology contributed at a significance level of $P < 0.05$. The preceding outcomes and arguments led to the model presented in Figure 1.

The standardised theoretical association between the dependent and independent variables is illustrated in Equation 1.

Figure 1: Fitted structural model

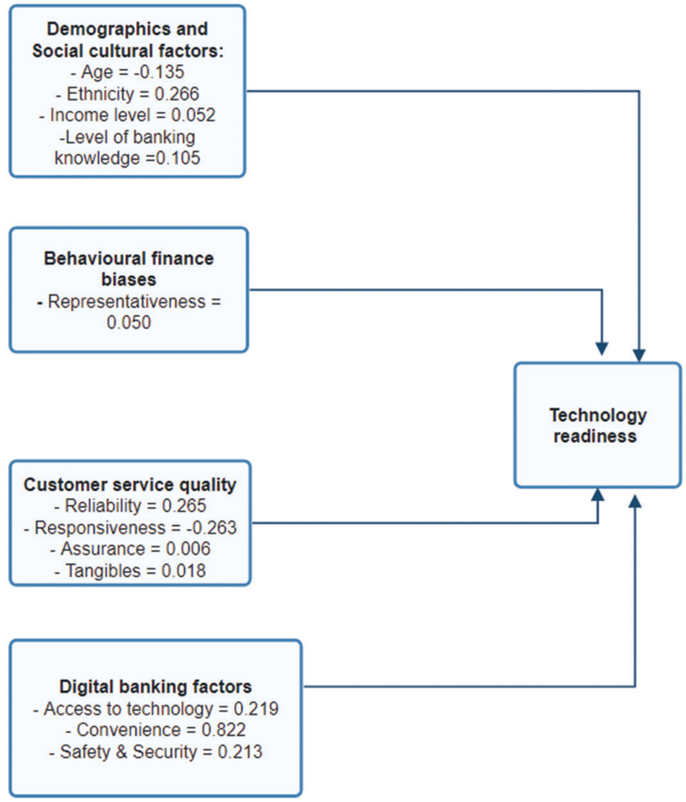

Table 2: Parameter estimates and *P* values of the structural model

Constructs			Parameter estimate	P
Technological readiness	Demographic and socio-cultural factors			
	‹‹‹	Age	−0.135	<0.001***
	‹‹‹	Gender	0.010	0.880
	‹‹‹	Ethnicity	0.266	0.018**
	‹‹‹	Education attainment	0.018	0.463
	‹‹‹	Income level	0.052	0.021**
	‹‹‹	Level of banking knowledge	0.105	0.027**
	Behavioural biases			
	‹‹‹	Anchoring	−0.040	0.142
	‹‹‹	Availability bias	−0.006	0.873
	‹‹‹	Gambler's fallacy	0.026	0.423
	‹‹‹	Loss aversion	−0.035	0.160
	‹‹‹	Mental accounting	0.007	0.779
	‹‹‹	Overconfidence	−0.035	0.297
	‹‹‹	Regret aversion	0.032	0.201
	‹‹‹	Representativeness	0.050	0.070*
	‹‹‹	Self-control	−0.011	0.753
	Customer service quality			
	‹‹‹	Reliability	0.265	0.309
	‹‹‹	Empathy	0.065	0.686
	‹‹‹	Responsiveness	−0.263	0.118
	‹‹‹	Assurance	0.006	0.965
	‹‹‹	Tangibles	0.018	0.941
	Customer preference for traditional or digital banking factors			
	‹‹‹	Access to technology	0.219	0.017**
	‹‹‹	Confidence in technology	2.098	0.388
	‹‹‹	Convenience	0.822	<0.001***
	‹‹‹	Perceived usefulness	−0.619	0.402
	‹‹‹	Safety & Security	0.213	<0.001***
	‹‹‹	Technological advances	−0.292	0.645
	‹‹‹	Trust	0.195	0.624

***Variable is significant at a 0.001 level (2-tailed) **Variable is significant at a 0.05 level (2-tailed) *Variable is significant at a 0.1 level (2-tailed)

Table 3: Interpretation of the variables in the model

	Constructs	Relationship	Interpretation in the model
Technological readiness	Demographic and socio-cultural factors		
	Age	inverse	An increase in age is linked with a decrease in technological readiness. Therefore, younger customers are more optimistic about new technological innovations.
	Income level	linear	An increase in income level is associated with an increase in technological readiness. Therefore higher-earning customers are more receptive to new technological innovations.
	Level of financial knowledge	linear	An increase in the level of banking knowledge is allied with an increase in technological readiness. Therefore, financially knowledgeable customers are more open to exploring new technology.
	Behavioural biases		
	Representativeness	linear	An increase in representativeness is associated with an increase in technological readiness. Customers organise new information to make financial decisions based on their perceptions of their previous technological experiences.
	Customer service quality		
	Reliability	linear	An increase in reliability is associated with an increase in technological readiness. Hence the more reliable the service quality of AI products, the more favourable attitude toward adopting AI.
	Responsiveness	Inverse	A decrease in responsiveness is associated with a reduction in technological readiness. Therefore, the less responsive the service quality of AI products, the less favourable attitude toward adopting AI
	Assurance	linear	An increase in assurance is associated with an increase in technological readiness. Hence, the more assuring the service quality, the more favourable attitude toward adopting AI.
	Tangibles	linear	An increase in tangibles is associated with an increase in technological readiness. Hence, the better the physical participation of an organisation in service offerings, the more favourable attitude toward adopting AI.
	Customer preference for traditional or digital banking factors		
	Access to technology	linear	An increase in access to technology is related to an increase in technological readiness. Better access to technology leads to the adoption of new technological innovations.
	Convenience	Linear	An increase in convenience is associated with an increase in technological readiness—convenience in technology results in the adoption of new technological innovations by customers.
	Safety and Security	Linear	An increase in safety and security is associated with an increase in technological readiness. Improved safety and security lead to the adoption of new technological innovations from customers.

$$
\begin{aligned}
Y_{TR} = & -0.135X_{age} + 0.266X_{ethnicty} + 0.052X_{income\,level} \\
& +0.105X_{level\,of\,banking\,knowledge} + 0.050X_{representativeness} \\
& +0.265X_{reliability} - 0.263X_{responsivenss} + 0.006X_{assurance} \\
& +0.018X_{tangibles} + 0.219X_{access\,to\,technology} \\
& +0.822X_{convenience} + 0.213X_{safety\,\&\,security}
\end{aligned} \quad (1)
$$

4.2.2. Model conclusion and recommendations

Kline (2014) emphasises the significance of presenting a notable conclusion and valuable recommendations for future research concerning the forecasting model. Henceforth, Table 3 offers an overview of the elements contributing to adopting AI banking products.

It may be concluded from Table 3 that demographic parameters such as income level, age, ethnicity, and banking expertise have a substantial impact on the adoption of AI banking products and, more importantly, are congruent with the findings of established researchers such as Nasri (2011), Achieng and Ingari (2015), Ramavhona and Mokwena (2016:6) and Khan et al. (2017) In contrast, it is intriguing to see that demographic parameters such as gender and educational attainment did not exhibit a statistically significant relationship with customers' readiness to adopt AI, which contradicts earlier research studies of Venkatesh et al. (2003), Riquelme and Rios (2010), Belanche et al. (2019), Eichhorn et al. (2020) and Sitienei (2020). In addition, representativeness bias was identified as the sole statistically significant behavioural finance basis. This could be due to the sample size used.

Regarding the customer service quality dimension, it was found that non were statistically significant in the sample, however intuitively and due to the arguments raised by researchers such as Coetzee et al. (2013) that dimensions including assurance, reliability, responsiveness and tangibles contribute to the adoption of technological innovations. Concerning the customers' preference for traditional or digital banking factors, it is worth noting that the dimensions, including access to technology, convenience, safety and security, were statistically significant in the sample. The model found that trust and perceived usefulness were not statistically significant.

5. CONCLUSION

Banks are entering a more competitive technological intelligence age. This competition forces them to redefine their daily processes, create innovative products, and ultimately transform customer experiences The rapid evolution of FinTech is a driving force behind today's AI-driven digital age. Biometrics, virtual assistants, and humanoid robots are all examples of AI technologies that, when applied after risks have been mitigated, may often outperform human decision-making in terms of speed and accuracy. However, customers may have varying perceptions of the services that AI technology in fintech may offer, while customers' satisfaction with banks' efficiency may be seen as a more imperative service.

In the results, demographical and socio-cultural variables like age revealed that younger customers are more optimistic about new technological innovations than their elder counterparts. It was also discovered that ethnicity substantially influences the adoption of new technology. Where customers with more substantial financial or banking knowledge are more receptive to new technology advancements such as AI banking products. Furthermore, some level of banking knowledge and income influence technology adoption. These findings correspond to the primary hypotheses and consensus of previous research studies that found in Africa, particularly in South Africa, a substantial discrepancy in living conditions between the poor and the wealthy, and the affluent effortlessly adapt to technological advances. The findings correspond with the general postulation that demographic and socio-cultural variables influence the adoption of new technology.

In contrast, it is intriguing that demographic parameters such as gender and educational attainment did not correlate statistically with customers' readiness to adopt AI. This contradicts the general postulation that gender influences new technology, such as AI. Regarding behavioural finance biases, only representativeness was statistically significant, demonstrating that customers organise new information to make financial decisions based on their views of prior technology encounters. It was also found that knowledge about finance, reliability, security and income level of banking customers influence bank customers' readiness for AI banking products. Concerning customer preference for traditional or digital banking factors, better technological access leads to the ease of adapting to new technological innovations. However, the country's digital gap limits its rapid digital development. This is because larger cities and metropolitan regions have highly sophisticated technology and infrastructure. Meanwhile, townships, smaller towns, and rural areas lack access to the most fundamental technologies. Furthermore, convenience in technology results in the adoption of new technological innovations by customers. Lastly, improved safety and security lead to the adoption of new technological innovations from customers.

This study aims to contribute to the research and banking fraternity. During this research endeavour, the researcher experienced some limitations and recommendations were provided. Future researchers can expand on the sample size although this study met the sample adequacy as recommended by previous researchers. Accordingly, future researchers should consider including more variables such as macroeconomic factors. Additionally, theoretical frameworks such as the digital readiness indexes can be incorporated.

REFERENCES

Achieng, B.M., Ingari, B.K. (2015), Factors influencing the adoption of mobile banking in Kenya's commercial banks: A case of Kenya commercial bank (KCB) Kilindini branch. International Journal of Scientific and Research Publications, 5(10), 1-14.

Aisyah, M. (2018), Islamic bank service quality and its impact on Indonesian customers' satisfaction and loyalty. Al-Iqtishad Journal of Islamic Economics, 10(2), 367-388.

Ajzen, I., Fishbein, M. (1975), A Bayesian analysis of attribution processes. Psychological Bulletin, 82(2), 261-277.

Akhtar, S., Irfan, M., Sarwar, A., Asma, S., Rashid, Q.U.A. (2019), Factors influencing individuals' intention to adopt mobile banking in China and Pakistan: The moderating role of cultural values. Journal of Public Affairs, 19(1), 1884.

Al-Azawei, A. (2019), The moderating effect of gender differences on learning management systems (less) acceptance: A multi-group analysis. Italian Journal of Educational Technology, 27(3), 257-278.

Alhkami, A.A., Alarussi, A.S. (2016), Service quality dimensions and customer satisfaction in telecommunication companies. Asian Journal of Business and Management, 4(3), 117-126.

Arner, D., Barberis, J., Buckley, R. (2015), The Evolution of Fintech: A New Post-Crisis Paradigm? University of New South Wales Law Research Series, Paper No. 2015/047. Available from: https://www.law.unsw.edu.au/research/faculty-publications [Last accessed on 2018 Mar 04].

Belanche, D., Casaló, L.V., Flavián, C. (2019), Artificial intelligence in fintech: Understanding robo-advisors adoption among customers. Industrial Management and Data Systems, 119(7), 1411-1430.

Berndt, A., Saunders, S., Petzer, D.J. (2010), Readiness for banking technologies in developing countries. Southern African Business Review, 14(3), 47-76.

Bhardwaj, P. (2019), Types of sampling in research. Journal of the Practice of Cardiovascular Sciences, 5(3), 157.

Biswas, S., Carson, B., Chung, V., Singh, S., Thomas, R. (2020), AI-bank of the Future: Can Banks Meet the AI Challenge? New York: McKinsey & Company.

Buente, W., Robbin, A. (2008), Trends in internet information behaviour, 2000–2004. Journal of the American Society for Information Science and Technology, 59(11), 1743-1760.

Chakiso, C.B. (2019), Factors affecting attitudes towards the adoption of mobile banking: Users and non-users perspectives. EMAJ: Emerging Markets Journal, 9(1), 54-62.

Chen, W. (2013), Internet use, online communication, and ties in Americans' networks. Social Science Computer Review, 31(4), 404-423.

Chung, K.C. (2014), Gender, culture and determinants of behavioural intents to adopt mobile commerce among the y generation in transition economies: Evidence from Kazakhstan. Behaviour and Information Technology, 33, 743-756.

Coetzee, J. (2009), Personal or remote interaction? Banking the unbanked in South Africa. South African Journal of Economic and Management Sciences, 12(4), 448-461.

Coetzee, J. (2018a), Strategic implications of fintech on South African retail banks. South African Journal of Economic and Management Sciences, 21(1), 1-23.

Coetzee, J. (2018b), Trust in banking relationships: Lessons for South African banks on bank selection in Saudi Arabia. Journal for New Generation Sciences, 16(2), 1-29.

Coetzee, J., Van Zyl, H., Tait, M. (2013), Perceptions of service quality by clients and contact personnel in the South African retail banking sector. Southern African Business Review, 17(1), 1-22.

Dilek, S., Çakır, H., Aydın, M. (2015), Applications of artificial

intelligence techniques to combating cyber crimes. International Journal of Artificial Intelligence and Applications, 6(2), 21-39.
Dupagne, M., Salwen, M.B. (2005), Communication technology adoption and ethnicity. The Howard Journal Communications, 16(1), 21-32.
Eichhorn, T., Jürss, S., Hoffmann, C. (2020), Dimensions of digital inequality in the sharing economy. Information, Communication and Society, 25(3), 395-412.
Fakhry, B. (2016), A literature review of behavioural finance. Journal of Economics Library, 3(3), 458-465.
Fan, X. (2007), Structural equation modeling. In: Ritzer, G, editor. The Blackwell Encyclopedia of Sociology. United States: Wiley.
Giovanis, A.N., Athanasopoulou, P. (2018), Consumer-brand relationships and brand loyalty in technology-mediated services. Journal of Retailing and Consumer Services, 40, 287-294.
Gupta, V.S., Garg, R. (2015), Technology readiness index of e-banking users: Some measurement and sample survey evidence. IUP Journal of Bank Management, 14(4), 43-58.
Hakeem, G., Ratnasari, R.T. (2021), Pengaruh perceived ease of use pada aplikasi m-banking bank umum Syariah dengan trust sebagai variabel intervening. Jurnal Ekonomi Syariah Teori dan Terapan, 8(6), 696-705.
Hammersley, M. (2012), What is Qualitative Research? Bloomsbury: Bloomsbury Publishing.
Hardy, M., Bryman, A. (2004), Handbook of Data Analysis. London: SAGE.
Hesamzadeh, M. (2021), Complete investigation about different factors that affecting the mobile bank applications. Journal of Mobile Computing, Communications and Mobile Networks, 7(3), 10-17.
Hesse, M. (2018), How Banks can Thrive in the Fintech Age, Personal Finance. Available from: https://www.iol.co.za/personal-finance/how-banks-can-thrive-in-the-fintech-age-15690270 [Last accessed on 2018 Oct 31].
Hoo, W.C., Yan, J.O.K., Liang, T.P., Ng, A.H.H. (2021), Age as moderator between factors influencing and adoption of e-wallet in Malaysia. Review of International Geographical Education Online, 11(8), 1143-1153.
Hyland, L., Sebastian, A., Seetharam, Y. (2021), An application of behavioural finance in banking: The discovery bank case. Journal of Economic and Financial Sciences, 14(1), 10.
Jackson, L.A., Zhao, Y., Kolenic, A. 3rd, Fitzgerald, H.E., Harold, R., Von Eye, A. (2008), Race, gender, and information technology use: The new digital divide. CyberPsychology and Behavior, 11(4), 437-442.
Jain, R., Jain, P., Jain, C. (2015), Behavioral biases in the decision-making of individual investors. IUP Journal of Management Research, 14(3), 7-27.
Jubraj, R., Graham, T., Ryan, E. (2018), Redefine Banking with Artificial Intelligence. Available from: https://www.accenture.com/gb-en/insight-ai-redefine-banking#zoom=50 [Last accessed on 2021 Sep 12].
Kazi, A.K. (2013), An empirical study of factors influencing adoption of Internet banking among students of higher education: Evidence from Pakistan. International Journal of Finance and Banking Studies, 2(2), 87-99.
Khan, A.P., Khan, S., Xiang, I.A.R. (2017), Factors influencing consumer intentions to adopt online banking in Malaysia. Business and Economic Review, 9(2), 101-134.
Kim, C., Mirusmonov, M., Lee, I. (2010), An empirical examination of factors influencing the intention to use mobile payment. Computers in Human Behavior, 26(3), 310-322.
Kim, D., Chun, H., Lee, H. (2014), Determining the factors that influence college students' adoption of smartphones. Journal of the Association for Information Science and Technology, 65(3), 578-588.
Kline, P. (2014), An Easy Guide to Factor Analysis. London: Routledge.
Kourtidis, D., Šević, Ž., Chatzoglou, P. (2011), Investors' trading activity: A behavioural perspective and empirical results. The Journal of Socio-Economics, 40(5), 548-557.
Kumar, K.N., Balaramachandran, P.R. (2018), Robotic process automation-a study of the impact on customer experience in retail banking industry. Journal of Internet Banking and Commerce, 23(3), 1-27.
Kurzweil, R., Richter, R., Kurzweil, R., Schneider, M. (1990), The Age of Intelligent Machines. Cambridge: MIT Press.
Laumer, S., Eckhardt, A., Trunk, N. (2010), Do as your parents say? - Analysing it adoption influencing factors for full and under-age applicants. Information Systems Frontiers, 12(2), 169-183.
Lee, H.J. (2017), Personality determinants of need for interaction with a retail employee and its impact on self-service technology (SST) usage intentions. Journal of Research in Interactive Marketing, 11(3), 214-231.
Liao, Z., Cheung, M.T. (2002), Internet-based e-banking and consumer attitudes: An empirical study. Information and Management, 39(4), 283-295.
Lopez, M.H., Gonzalez-Barrera, A., Patten, E. (2013), Closing the Digital Divide: Latinos and Technology Adoption. Available from: https://deseg.tusd1.org/Portals/TUSD1/Deseg/docs/AR15/AppendixII-25.pdf [Last accessed on 2021 Sep 12].
Lu, Y., Yang, S., Chau, P.Y., Cao, Y. (2011), Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. Information and Management, 48(8), 393-403.
Malhotra, N.K., Nunan, D., Birks, D.F. (2017), Marketing Research: An Applied Approach. 5th ed. England: Pearson.
Mamina, R., Maziriri, E.T. (2020), Modelling consumers' willingness to use card-less banking services: An integration of TAM and TPB. International Journal of Business and Management Studies, 12(1), 241-257.
Marakarkandy, B., Yajnik, N., Dasgupta, C. (2017), Enabling internet banking adoption. Journal of Enterprise Information Management, 30(2), 263-294.
Marangunić, N., Granić, A. (2015), Technology acceptance model: A literature review from 1986 to 2013. Universal Access in the Information Society, 14(1), 81-95.
Masinge, K. (2010), Factors Influencing the Adoption Of Mobile Banking Services at the Bottom of the Pyramid in South Africa. Pretoria: University of Pretoria. (Thesis -PhD).
Masocha, R., Chiliya, N., Zindiye, S. (2011), The impact of technology on competitive marketing by banks: A case study approach. African Journal of Marketing Management, 3(3), 68-77.
Mellenbergh, G.J. (2019), Counteracting Methodological Errors in Behavioral Research. Switzerland: Springer International Publishing.
Mohammadi, H. (2015), Investigating users' perspectives on e-learning: An integration of TAM and is success model. Computers in Human Behavior, 45, 359-374.
Moro, S., Cortez, P., Rita, P. (2015), Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation. Expert Systems with Applications, 42(3), 1314-1324.
Mueller, R.O., Stapleton, L.M., Hancock, G.R. (2019), The Reviewer's Guide to Quantitative Methods in the Social Sciences. 2nd ed. New York: Routledge.
Musyaffi, A.M., Mulyani, S., Suraida, I., Sukmadilaga, C. (2021), Lack of readiness of digital banking channel acceptance: Study on Tam 3 and technology readiness. Academy of Strategic Management Journal, 20(4), 1-18.
Namahoot, K.S., Laohavichien, T. (2015), Quality management and trust of internet banking in Thailand. International Journal of Scientific

and Technology Research, 4(9), 257-262.
Nasri, W. (2011), Factors influencing the adoption of internet banking in Tunisia. International Journal of Business and Management, 6(8), 143-160.
Ngai, E.W., Poon, J., Chan, Y.H. (2007), Empirical examination of the adoption of WebCT using tam. Computers and Education, 48(2), 250-267.
Odusina, A.O. (2014), Automated teller machine usage and customers satisfaction in Nigeria. Global Journal of Management and Business Research, 2(3), 43-47.
Ono, H., Zavodny, M. (2007), Digital inequality: A five country comparison using microdata. Social Science Research, 36(3), 1135-1155.
Pakurár, M., Haddad, H., Nagy, J., Popp, J., Oláh, J. (2019), The service quality dimensions that affect customer satisfaction in the Jordanian banking sector. Sustainability, 11(4), 1113.
Pallant, J. (2013), SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS. 5th ed. England: McGraw Hill.
Pallant, J. (2020), SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS. 7th ed. England: McGraw Hill.
Parasuraman, A. (2000), Technology readiness index (tri) a multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research, 2(4), 307-320.
Parasuraman, A., Berry, L.L., Zeithaml, V.A. (1991), Understanding customer expectations of service. Sloan Management Review, 32(3), 39-48.
Parasuraman, A., Colby, C.L. (2015), An updated and streamlined technology readiness index: Tri 2.0. Journal of Service Research, 18(1), 59-74.
Parasuraman, A., Zeithaml, V., Berry, L. (1988), SERVQUAl: A multiple-item scale for measuring consumer perceptions. Journal of Retailing, 64(1), 12-37.
Parasuraman, A., Zeithaml, V.A., Berry, L.L. (1994), Reassessment of expectations as a comparison standard in measuring service quality: Implications for further research. Journal of Marketing, 58(1), 111-124.
Park, J.Y., Ryu, J.P., Shin, H.J. (2016), Robo advisors for portfolio management. Advanced Science and Technology Letters, 141(1), 104-108.
Paschen, J., Kietzmann, J., Kietzmann, T.C. (2019), Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. Journal of Business and Industrial Marketing, 34(7), 1410-1419.
Payne, E.M., Peltier, J.W., Barger, V.A. (2018), Mobile banking and ai-enabled mobile banking: The differential effects of technological and non-technological factors on digital natives' perceptions and Behavior. Journal of Research in Interactive Marketing, 12(3), 328-346.
Pham, L.T.M. (2018), Qualitative Approach to Research a Review of Advantages and Disadvantages of Three Paradigms: Positivism, Interpretivism and Critical Inquiry. Australia: University of Adelaide.
Plucker, J.A. (2003), Exploratory and confirmatory factor analysis in gifted education: Examples with self-concept data. Journal for the Education of the Gifted, 27(1), 20-35.
Pompian, M.M., Wood, A.S. (2006), Behavioral Finance and Wealth Management: How to Build Optimal Portfolios for Private Clients. New Jersey: John Wiley and Sons, Inc.
Poole, D.L., Mackworth, A.K. (2010), Artificial Intelligence: Foundations of Computational Agents. Cambridge: Cambridge University Press.
Quinlan, C. (2011), Business Research Methods. Hampshire: Cengage Learning.
Ramavhona, T.C., Mokwena, S. (2016), Factors influencing internet banking adoption in South African rural areas. South African Journal of Information Management, 18(2), 1-8.
Ramli, Y., Harwani, Y., Soelton, M., Hariani, S., Usman, F., Rohman, F. (2021), The implication of trust that influences customers' intention to use mobile banking. The Journal of Asian Finance, Economics, and Business, 8(1), 353-361.
Redda, E.H. (2015), Electronic Banking Services in South Africa: Service Quality Scale Development and Validation. Vanderbijlpark: North-West University. (Thesis -PhD).
Rekarti, E., Hertina, L. (2014), Some factors that affect the interest in buying online on tokobagus buying and selling sites. Journal of Economic and Social Sciences, 2(3), 311-318.
Riquelme, H.E., Rios, R.E. (2010), The moderating effect of gender in the adoption of mobile banking. International Journal of Bank Marketing, 28(5), 328-341.
Robinson, L., Cotten, S.R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W., Stern, M.J. (2015), Digital inequalities and why they matter. Information, Communication and Society, 18(5), 569-582.
Rossini, L., Maree, J. (2010), Business Management for Financial Planners: A Guide to Creating a Sustainable Service-Based Financial Planning Business. Claremont: Juta and Company Ltd.
Roy, S., Moorthi, Y. (2017), Technology readiness, perceived ubiquity and m-commerce adoption: The moderating role of privacy. Journal of Research in Interactive Marketing, 11(3), 268-295.
Sathiyavany, N., Shivany, S. (2018), E-banking service qualities, e-customer satisfaction, and e-loyalty: A conceptual model. The International Journal of Social Sciences and Humanities Invention, 5(6), 4808-4819.
Schumacker, R.E., Lomax, R.G. (2004), A Beginner's Guide to Structural Equation Modeling. New Jersey: Lawrence Erlbaum Associates.
Shaw, N., Sergueeva, K. (2016), Convenient or Useful? Consumer Adoption of Smartphones for Mobile Commerce. Available from: https://aisel.aisnet.org/digit2016/3 [Last accessed on 2021 Dec 11].
Sitienei, M. (2020), Leveraging Robotic Process Automation as an Enabler of Organisational Digital Transformation: A Case of a Telecommunication Company in Kenya. Nairobi: University of Nairobi. (Thesis - PhD).
Slade, E.L., Dwivedi, Y.K., Piercy, N.C., Williams, M.D. (2015), Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust. Psychology and Marketing, 32(8), 860-873.
Sleiman, K.A.A., Juanli, L., Lei, H., Liu, R., Ouyang, Y., Rong, W. (2021), User trust levels and adoption of mobile payment systems in China: An empirical analysis. Sage Open, 11(4), 21582440211056599.
Sreedevi, V. (2013), E-banking and cheque truncation system (CTS). Indian Journal of Applied Research, 3(2), 184-186.
StatsSa. (2020), How Unequal is South Africa? Available from: https://www.statssa.gov.za/?p=12930 [last accessed on 2020 May 22].
Takemura, K. (2014), Behavioral Decision Theory. Psychological and Mathematical Descriptions of Human Choice Behavior. Japan: Springer.
Thompson, S.K. (2012), Sampling. 3rd ed. New Jersey: John Wiley & Sons.
Thowfeek, M.H., Mirzan, S.H. (2017), The factors influencing customers' decision to adopt internet banking in Sri Lanka. Journal of Information Systems and Information Technology (JISIT), 2(2), 1-9.
Ullman, J.B., Bentler, P.M. (2012), Structural equation modeling. In: Weiner, I., Schinka, J.A., Velicer, W.F., editors. Handbook of Psychology. 2nd ed. United States: John Wiley & Sons.
Van Deursen, A.J.A.M., Van Dijk, J.A.G.M., Peters, O. (2011), Rethinking internet skills: The contribution of gender, age, education, internet experience, and hours online to medium-and content-related internet skills. Poetics, 39(2), 125-144.
Van Dyk, R., Van Belle, J.P. (2019), Factors Influencing the Intended Adoption of Digital Transformation: A South African case study. In: 2019 Federated Conference on Computer Science and Information

Systems (FedCSIS). IEEE. p. 519-528.
Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D. (2003), User acceptance of information technology: Toward a unified view. MIS Quarterly, 27, 425-478.
Watt, B. (2017), The Rise of mPOS: How Mobile Point-of-sale is Transforming the Hospitality Industry. Available from: https://www.paycorp.co.za/rise-mpos-mobile-point-sale-transforming-hospitality-industry [Last accessed on 2019 Aug 10].
Worku, G., Tilahun, A., Tafa, M. (2016), The impact of electronic banking on customers' satisfaction in Ethiopian banking industry (the case of customers of Dashen and Wogagen banks in Gondar city). Journal of Business and Financial Affairs, 5(2), 2-18.
Yadav, S.K., Singh, S., Gupta, R. (2019), Biomedical Statistics. Singapore: Springer.
Yale, L., Venkatesh, A. (1986), Toward the construct of convenience in consumer research. Association for Consumer Research, 13, 403-408.
Yao, M., Zhou, A., Jia, M. (2018), Applied Artificial Intelligence: A Handbook for Business Leaders. New York: Topbots Inc.
Yuan, S., Hussain, S.A., Hales, K.D., Cotten, S.R. (2016), What do they like? Communication preferences and patterns of older adults in the United States: The role of technology. Educational Gerontology, 42(3), 163-174.
Yussaivi, A.M., Lu, C.Y., Syarief, M.E., Suhartanto, D. (2021), Millennial experience with mobile banking and artificial intelligence (AI)-enabled mobile banking: Evidence from Islamic banks. International Journal of Applied Business Research, 3(1), 39-53.
Zolait, A.H.S., Mattila, M., Sulaiman, A. (2009), The effect of user's informational-based readiness on innovation acceptance. International Journal of Bank Marketing, 27(1), 76-100.