Behavioural Biases Influencing Technology Adoption by South African Bank Customers

L. Garekwe¹, Suné Ferreira-Schenk²*, Zandri Dickason-Koekemoer²

¹ Ph.D., Faculty of Economics and Management Sciences, North-West University, South Africa
² Ph.D., Professor, North-West University, South Africa

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Abstract:
Artificial intelligence technology has the potential to accelerate the financial industry's transformation by offering tailor-made products and services and improving customer experience. This transformation could give banks in South Africa a competitive advantage in the market and globally. This paper aimed to identify the behavioral biases that influence customers' readiness and adoption of innovative technology within their bank. Under a positivist paradigm, nonprobability convenience and snowball sampling were used to collect the data using an online questionnaire. The sample size consisted of 346 banking customers in South Africa. Using factor analysis (EFA), the study found that customers exhibit three dimensions: optimism, innovativeness, and insecurity, which describe technology readiness as a psychological state in which individuals are ready to accept new technology. Additionally, using descriptive and correlation analysis, the findings indicated that customers exhibit overconfidence, anchoring, and loss aversion as the main behavioral biases influencing new technology adoption within banks. The empirical findings of this study are essential as they provide South African banks and risk managers with improved insights and comprehension regarding the profile of customers who may be ready to adopt artificially intelligent banking products. Furthermore, it is recommended that future research follow a mixed-methods approach by also incorporating qualitative interviews to examine the rationales as to why certain behavioral finance biases influence the adoption of AI and others not.

Keywords: behavioral biases, artificial intelligence, technology, technological readiness, South Africa.

影响南非银行客户技术采用的行为偏见

Corresponding Author: Professor Suné Ferreira-Schenk, Ph.D., North-West University, South Africa; email: 23261048@nwu.ac.za

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1. Introduction

The evolution of banks as institutions of organizing and protecting customers’ financial interests has pioneered the involvement of technology to drive business value (Jubraj et al., 2018). In the financial business domain, the core operations of banks as financial institutions are to issue loans, manage deposits and investments, and perform other activities (Moro et al., 2015). The banking history stems from when ancient empires required payment for goods and services, where coins and metals served as exchange. However, these materials had to be stored in safe places such as banks (Davies & Green, 2010).

The evolution of technology in banking is over 180 years old (Moro et al., 2015). In 1836, a pneumatic capsule was used for transmitting telegrams. Banks appreciated the innovation, enabling customers to deposit and withdraw funds using drive-ins (Judd, 2017). According to Dougles (2018), the original universal credit card emerged in the 1950s to provide convenient payment solutions to customers before the famous automated teller machine (ATM) was introduced in 1967 (Odusina, 2014). Since then, several innovations have emerged, such as digital displays, credit cards, and algorithms that associate customers’ encoded Personal Identification Numbers (PIN) with accounts (Dougles, 2018). According to Sreedevi (2013), physical checks were initially introduced in the early 1600s. However, electronic check clearing systems were introduced only in the early 2000s. Electronic check systems enable images of physical checks to be made without moving the physical check. This innovation made instant payment options much more effortless (Asmah et al., 2018). In 2010 and 2015, mobile point-of-sale devices and EMV (Europay, Mastercard, and Visa) chip cards emerged, which brought customers the convenience of card payments in any location (Tsai et al., 2019). EMV card chips overlaid the security of card payments since the information was encrypted and tokenised before being transmitted (Watt, 2017).

Belanche et al. (2019) argue that the concept of fintech extends beyond electronic banking and the digitalization of customer experience. It develops and effectively introduces innovative technology products to address the changing financial expectations of customers. Additionally, Park et al. (2016) claim that artificially intelligent (AI) 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 (Ameen et al., 2021). This transformation gives those banks in South Africa that are adopting AI a competitive advantage in the market. AI within the banking industry articulates the development of intelligent machines that function and interact similarly to humankind (Kurzweil et al., 1990). The developments in increased computational resources, growth of data, and reasoning models have made the field of study captivating (Hammond, 2015). AI in fintech has reduced operational risks within banks by automating manual tasks deemed cumbersome (Yao et al., 2018). Chatbots and other realistic interactive interfaces can read the tone and context of a conversation through text and respond accordingly, allowing banks to streamline existing customer service processes (DiVanna, 2003). In 2018, Nedbank launched its first humanoid to attend to customers by offering bank-related solutions. Robo-advisor innovation is the most common phenomenon within fintech as these autonomous systems will reduce operational costs associated with traditional human advisory (Park et al., 2016).

Irrespective of the improvement within the banking industry, banks must maintain a focus on customer perception as the basis for service improvement and quality advancements, which is done by studying their customers’ banking and preference behaviour (Edvardsson & Ross, 2003). Additionally, a variety of decision-making biases have been documented by psychological research, which can manifest in various decision-making circumstances (Byrne & Utkus, 2013). The field of behavioral finance has evolved to understand better how emotions and cognitive biases influence decision-making throughout the decision process. According to Glaser et al. (2019), several studies in fintech have mainly focused on AI’s technical, legal, and revenue benefits in banking and exclusively ignored customers’ behavioural biases that influence their readiness for new technology. Thus, this
study identifies the behavioral biases that influence customers' readiness for new technology in banking products and services.

2. Literature Review

2.1. Behavioral Finance Biases

Fakhry (2016) states that financial decision-making environment is complex and ambiguous. However, when confronted with complexity, humans analyze information using cognitive and emotional processes, generating heuristics that enable individuals to simplify decision-making (Jain et al., 2015). While decision theory refers to consciousness's ability to make decisions, it may also be technically defined as choosing one option from various options (Takemura, 2014). In this regard, Hyland et al. (2021) assert that behavioral finance is primarily concerned with the influence of human irrationality on financial decisions. Behavioural finance theories also explain individuals’ behaviors that do not optimise anticipated utility (Pompian & Wood, 2006). Rossini and Maree (2010) claimed that behavioral finance studies the influence of human psychology on financial decision-making and motivating emotions. While traditional finance theories focus on how people act to maximize their wealth, behavioral finance theories focus on how customers genuinely behave in an economic environment (Kourtidis et al., 2011).

Moreover, traditional finance tries to explain financial decision-making by using markets and their participants (Virigineni & Rao, 2017). As depicted in Figure 1, when a customer makes financial decisions, behavioral finance involves financial knowledge, economics knowledge, and cognitive psychology understanding (Muradoglu & Harvey, 2012; Ferreira, 2018).

Psychological research has documented a range of decision-making biases. These biases may manifest in many decision-making aspects (Byrne & Utkus, 2013). Behavioural biases are classified into emotional and cognitive biases (Hyland et al., 2021).

2.1.1. Emotional Biases

Emotions are affective responses to an experience, event, or object (Kim, 2012). Emotional biases are systematic errors from rationality that occur during decision-making due to emotions (Hyland et al., 2021). The influence of emotional elements on the decision-making process is discernible in present emotions and disposition and the expectation of future emotions (Mazzoli & Marinelli, 2011). However, emotion and mood may be distinguished by the existence or absence of an event or object that elicited the individual's feelings (for example, emotions have objects of elicitation, but moods do not) (Parkinson et al., 1996). As a result, emotions are more strongly related to causation. In contrast, moods are longer-lasting affective states (Kim, 2012). As a result, affective states include psychological consequences that might influence an individual's decision-making (Pompian, 2016). As shown in Table 1, emotional biases include the following.

Table 1. Emotional biases (Pompian, 2012; Byrne & Utkus, 2013; Jain et al., 2015; Ferreira, 2018)

<table>
<thead>
<tr>
<th>Bias</th>
<th>Description</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-control</td>
<td>Self-control bias refers to humans' proclivities for today's consumption at the price of future savings. Self-control bias entails making trade-offs between one's current and future selves, with rewards not necessarily immediate and future advantages unclear. As a result, self-control affects various financial behaviors.</td>
<td>Pompian (2012); O'Donoghue and Rabin (2015); Xiao and Porto (2019)</td>
</tr>
<tr>
<td>Loss aversion</td>
<td>Loss aversion is a psychological term that refers to a person's inclination to prioritize avoiding losses above earning benefits owing to the perceived psychological cost of losses. As a result, individuals feel twice anguish when they lose something as they do when they acquire something.</td>
<td>Tversky and Kahneman (1991); Byrne and Utkus (2013); Ferreira (2018)</td>
</tr>
<tr>
<td>Regret aversion</td>
<td>Regret is often characterized as a &quot;bad feeling elicited by the knowledge that an alternative would have resulted in a better outcome; regret can therefore only be fully experienced after the fact, albeit it may be predicted before an action.</td>
<td>Jain et al. (2015)</td>
</tr>
<tr>
<td>Omission</td>
<td>When a choice results in a negative consequence compared to what may have been, people believe that the decision was worse if the outcome was the result of action rather than inactivity.</td>
<td>Ritov and Baron (1995); Kordes-de Vaal (1996)</td>
</tr>
<tr>
<td>Status quo</td>
<td>Emotional biases, such as the &quot;status quo,&quot; lead individuals to choose the option that maintains or extends the status quo over alternatives that might lead to a different outcome. In other words, status quo bias is seen in those who prefer that everything remains primarily the same.</td>
<td>Fleming et al. (2010); Pompian (2012)</td>
</tr>
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</table>

Pompian (2012) argued that emotional biases are more complex to overcome than cognitive biases stemming from deliberate decisions because emotional variables arise from instinctive reactions.
2.1.2. Cognitive Biases

Cognitive biases are a component of mental processes that restrict the capacity to cope with complex information to make the best choice, resulting in judgment mistakes (Ricciardi, 2008). Numerous studies on behavioral finance stem from cognitive psychology, which examines how individual investors think, argue, and execute financial choices (van den Bergh-Lindeque, 2021). Tversky and Kahneman (1991) created the concept of cognitive biases through their heuristics–biases approach, emphasizing ambiguous decisions. Cognitive biases refer to the systematic deviation from 'normative' behaviour. Tversky and Kahneman (1991) define heuristics as cognitive resource rules that explain how customers make financial choices, form judgments, and resolve issues once confronted with complex situations or little information. Through trial and error, individual investors often make investment options using the heuristic decision-making process (Hyland et al., 2021). Generally, these rules of cognitive resources work well. However, it may result in systemic cognitive biases or mistakes in specific situations (Subash, 2012). Factors of cognitive biases are displayed in Table 2.

<table>
<thead>
<tr>
<th>Bias</th>
<th>Description</th>
<th>Authors</th>
</tr>
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<tbody>
<tr>
<td>Overconfidence</td>
<td>Overconfidence may be described as the propensity to overestimate the likelihood of attaining one's aims due to a presumptuous conviction in one's talents or traits as they may be employed to affect the desired outcome. Confidence is necessary for success in several fields, from professional performance to sports.</td>
<td>Lunn (2013); Jain et al. (2015); Virigineni and Rao (2017); Ferreira (2018)</td>
</tr>
<tr>
<td>Herding</td>
<td>The herding effect is a phenomenon that occurs when individuals seek to fit in and hence replicate the behavior (rational or irrational) of others around them. In the absence of differentiation in choice-making, people follow the choices of different individuals without getting hysterical over the outcomes of specialized and essential assessments by professionals.</td>
<td>Thaler and Sunstein (2008); Jaiswal and Kamil (2012); Jain et al. (2015)</td>
</tr>
<tr>
<td>Hindsight</td>
<td>Hindsight is more likely to occur when a person feels that the commencement of a previous event was foreseeable and evident, whereas in reality, the occurrence could not have been appropriately foreseen. As a result, individuals continuously overstate what might be expected with sufficient forethought.</td>
<td>Pompian (2012); Jain et al. (2015)</td>
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<tr>
<td>Cognitive dissonance</td>
<td>Individuals encounter mental conflict once they obtain new information that contradicts their pre-existing ideas or shows their erroneous beliefs or assumptions. Dissonance is characterized by persons changing their opinions to adhere to their prior behaviours. Therefore, when people discover that their views and suspicions are incorrect, they experience a mental conflict.</td>
<td>Pompian (2012); Virigineni and Rao (2017); Sukumar and Metoyer (2018)</td>
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<tr>
<td>Anchoring</td>
<td>Anchoring describes the phenomenon of an individual's reliance on a specific piece of information while making financial decisions. As a result, anchoring is a psychological heuristic that affects how individuals infer probability.</td>
<td>Pompian and Wood (2006); Byrne and Utkus (2013); Sukumar and Metoyer (2018); Ferreira (2018)</td>
</tr>
<tr>
<td>Availability</td>
<td>It refers to humans' tendency to appraise the significance of information based on its recall ability; when individuals are required to estimate probabilities and evaluate the attractiveness of various choices, the availability bias results in systematic inaccuracies.</td>
<td>Pompian and Wood (2006); Byrne and Utkus (2013); Sukumar and Metoyer (2018)</td>
</tr>
<tr>
<td>Rationalisation</td>
<td>Rationalisation occurs when individuals' proclivities for developing an acceptable rationale for prior actions boost their decision-making abilities.</td>
<td>Mazzoli and Marinelli (2011)</td>
</tr>
<tr>
<td>Representativeness:</td>
<td>Representational bias is a term that relates to humans' proclivities for making judgments based on similarities or preconceptions. This may account for people's proclivity for extrapolating current success into the future.</td>
<td>Jain et al. (2015)</td>
</tr>
<tr>
<td>Confirmation</td>
<td>Confirmation bias is a kind of selective perception in which we value ideas that support our views more than those that contradict them. It is possible to think of confirmation bias as a selection bias in gathering information to support specific ideas.</td>
<td>Pompian and Wood (2006); Sukumar and Metoyer (2018)</td>
</tr>
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</table>

2.2. Technology Readiness

According to Parasuraman and Colby (2015) and Musyaffi et al. (2021), the idea of technological readiness is described as a customer's inclination to adopt and apply new technologies in transaction performance. According to van Dyk and Van Belle (2019), technology has accelerated transformation in the field of banking. This trend is expected to continue
as present technologies improve in speed, capacity, usefulness, and simplicity of use. However, as Parasuraman and Colby (2015) point out, customers are confronted with different trade-offs when maximizing 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. Furthermore, Melas et al. (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 & Moorthi, 2017). Additionally, Gupta and Garg (2015) state that TR is a four-dimensional construct comprised of the following dimensions:

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Definitions</th>
<th>Authors</th>
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<tbody>
<tr>
<td>Optimism</td>
<td>Optimism is a favorable attitude toward technology and the assumption that it provides individuals with improved control, flexibility, and efficiency. Therefore, optimism is a critical facilitator in determining technological readiness.</td>
<td>Parasuraman and Colby (2015);</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Musyaffi et al. (2021)</td>
</tr>
<tr>
<td>Innovativeness</td>
<td>Innovativeness is a natural inclination toward experimenting with innovation. Additionally, innovativeness is a facilitator in determining technological readiness.</td>
<td>Ramírez-Correa et al. (2020); Amer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>and Atheer (2022)</td>
</tr>
<tr>
<td>Discomfort</td>
<td>Discomfort refers to a sense of being overwhelmed by technology because of a lack of control. As a result, discomfort is an inhibitor to adopting new technologies.</td>
<td>Parasuraman and Colby (2015);</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Berndt et al. (2010); Ramírez-Correa et al. (2020)</td>
</tr>
<tr>
<td>Insecurity</td>
<td>Insecurity refers to skepticism about technology and doubts about its capacity to function correctly. Insecurity also serves as an inhibitor to technological readiness.</td>
<td>Parasuraman and Colby (2015);</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Musyaffi et al. (2021); Amer and</td>
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<td></td>
<td></td>
<td>Atheer (2022)</td>
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</tbody>
</table>

According to Illia et al. (2015), the dimensions above are independent of each other, with a person having facilitator and inhibitor attitudes toward one another. Additionally, 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 skeptical 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 ready (Gupta & Garg, 2015). Berndt et al. (2010), Parasuraman and Colby (2015), Gupta and Garg (2015), and Musyaffi et al. (2021) have established technological readiness. 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 utilize new technology.

3. Methodology

3.1. Population, Sample, and Sampling Method

The population consisted of banking customers within South African banks. However, given that time could not allow us to reach all banking customers, researchers considered the time and cost limitations associated with collecting information from the selected sample size. Therefore, this research examined a sample size of 346 South African banking customers, considering complete response rate, expenses, and time restrictions. The sample size is in line with the samples of comparable studies and satisfies the standards for the statistical analysis performed (Slade et al., 2015; Khan et al., 2017; Yussaiví et al., 2021). A sample of 346 participants was enough to produce accurate results, as Pallant (2013) recommends at least a sample size of 150 participants with a ratio of five items for each variable for successful factor analysis.

3.2. Research Instrument and Data Collection

Creswell (2014) states that any instrument or data collection method has a single overarching objective: to collect adequate primary data to enable the researcher to answer the research question. The data were acquired using an online self-administered questionnaire. The questionnaire design can substantially impact participants' responses and inclination to complete the questionnaire fully and correctly. In designing the questionnaire, the researchers carefully considered and precisely determined the data required with the essential knowledge concerning the fundamental phenomenon. As a result, the questionnaire was adequately designed to ensure its reliability and validity in obtaining the quantitative data needed for the research project (Quinlan et al., 2015). An appropriate, straightforward, enlightening cover letter was carefully designed and included all necessary information while encouraging participants to complete the questionnaire to obtain satisfactory response rates. A focus group of twelve participants pre-tested the questionnaire for this study. In addition, two of the twelve individuals were expert researchers in economics, marketing, and risk management to supervise any content or measurement errors. The remaining ten questionnaires were randomly allocated to customers with bank account access. Choosing 12 participants from the pre-test sample ensured that a varied range of age groups, races, and educational levels were represented. Overall, the average time required by all 12 participants to complete...
the exercise was 12 min, which falls within the acceptable period established by McDaniel and Gates (2018).

3.3. Statistical Analysis

First, factor analysis (EFA) was used to analyze factors of technological readiness. Second, descriptive analysis was conducted where the term "descriptive statistics" refers to processes that take raw data and arrange and simplify it more efficiently (Khalid et al., 2012; Gravetter et al., 2020). Quinlan et al. (2015) and Sekaran and Bougie (2016) classify descriptive statistics into three broad categories: central tendency measures, dispersion measures, and shape measures. Descriptive statistics were employed to accomplish this study’s empirical goal, which is to identify the behavioral biases that influence customers' readiness for new technology. Additionally, the behavioral biases that influence customers' technological readiness were identified through correlation analysis, which revealed a relationship between behavioral finance biases and financial decision-making on the part of the customers. A nonparametric Spearman's rho correlation was also used to examine the association between behavioral finance biases and technological readiness dimensions. Spearman's rho correlation coefficient with values ranging from -1.0 to +1.0 indicates the strength of the association. A correlation value of -1.0 indicates a perfect negative association, 0 indicates no association, and +1.0 indicates a perfect positive relationship. In addition, the following principles were used to estimate the strength of the association between behavioral finance biases and customer service quality dimensions. In addition, the subsequent hypotheses were formulated to evaluate the association between behavioral finance biases and the technological dimensions:

- $H_{01}$: There is no association between behavioral finance biases and optimism.
- $H_{a1}$: There is an association between behavioral finance biases and optimism.
- $H_{a2}$: There is no association between behavioral finance biases and insecurity.

4. Empirical Results and Discussion

4.1. Factor Analysis (EFA) of Technological Readiness

The questionnaire utilized EFA, a multivariate technique used to explore the essential items that best describe the readiness of customers to use new technology. As indicated in Table 4, KMO and Bartlett's sphericity tests yielded satisfactory results of the factor analysis in the technological readiness section of the questionnaire. The KMO index was 0.842, more significant than the minimum threshold of 0.5, and may be considered sufficient sampling adequacy (Sarstedt & Mooi, 2019). The chi-square result for Bartlett's test of sphericity was around 1532.151 with 105 degrees of freedom and was statistically significant ($p < 0.001$), which is less than 0.05. As a result, this indicated that the data were eligible for factor analysis. Furthermore, the following subsection discusses identifying and interpreting the factors and the internal reliability test for technological readiness.

4.1.1. Identification and Interpretation of Factors of Technological Readiness

From Table 4, three factors with eigenvalues greater than 1.0 were identified and elucidated 52.348% of the total variance. As a result, these factors were deemed adequate for describing the customers' readiness for AI technology. In line with the theories discussed in the literature review, the following factors of technological readiness were identified.

### Table 4. Pattern matrix for technological readiness constructs

<table>
<thead>
<tr>
<th>Item</th>
<th>Optimism</th>
<th>Innovativeness</th>
<th>Insecurity</th>
</tr>
</thead>
<tbody>
<tr>
<td>I use e-wallets and instant money when sending money to someone</td>
<td>0.779</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use my bank app to purchase airtime, electricity, etc.</td>
<td>0.651</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use non-contact payment options when paying for goods or services</td>
<td>0.587</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use online tools (internet banking, bank app) to apply for bank products (loan)</td>
<td>0.543</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use my bank app to make online payments (utility, account, etc.)</td>
<td>0.520</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use my fingerprint detection to open my bank app</td>
<td>0.474</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I will use online communication platforms (Twitter, WhatsApp) to communicate with my bank</td>
<td>0.795</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am willing to use contactless payment options (Zapper, Snapscan etc.) to settle bills</td>
<td>0.757</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am open to using intelligent robots (chatbots) as financial advisors and tellers.</td>
<td>0.748</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am willing to use paperless banking to apply for bank products (loans, credit cards, vehicle finance etc.)</td>
<td>0.707</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am ready to use facial recognition and fingerprint detection as personal identification tools for banking</td>
<td>0.666</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use the ATM to get my statements</td>
<td>0.787</td>
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</table>
Factor one, optimism, consisted of six items that elucidated 30.844% of the variance with an eigenvalue of 4.627. The elements loaded into this factor demonstrate customers' favorable attitudes toward technology. Factor two, innovativeness, consisted of five items that elucidated 11.776% of the variance with an eigenvalue of 1.766. The elements loaded into this factor demonstrate the customers' natural inclination toward experimenting with innovation. Factor three, insecurity, consisted of four items that elucidated 9.728% of the variance with an eigenvalue of 1.459. The elements loaded into this factor indicate the customers’ skepticism about technology and doubts that it may pose a risk of financial loss.

### 4.1.2. Internal Reliability of Technological Readiness

Cronbach’s alpha values were determined for each of the three factors of technological readiness in the questionnaire to verify the internal consistency of this section. Henceforth, Table 6 provides Cronbach’s alpha coefficient values and the average interitem correlation per dimension of technological readiness. The three extracted factors produced appropriate Cronbach’s alpha values greater than 0.6. Factors one, optimism, and three, insecurity, yielded the Cronbach alphas of 0.683 and 0.676, showing reasonable reliability and an ideal average inter-item correlation of 0.294 and 0.378, respectively. In addition, factor two, innovativeness, demonstrated good reliability with Cronbach’s alpha value of 0.798, with an ideal interitem correlation of 0.461. Therefore, the questionnaire’s technological readiness scale has satisfactory internal consistency and is consequently considered reliable.

### 4.2. Descriptive Statistics

Descriptive statistics, namely percentages, frequencies, measures of dispersion, and central tendency, were used to ascertain the behavioral biases influencing customers' financial decision-making. This addresses the third empirical objective. The degree to which behavioral finance biases influence customers' financial choices was determined using a six-point Likert scale (1 = strongly disagree, 6 = strongly agree). For the representativeness bias, most of the sample (70.7%) recorded that they somewhat agreed to strongly agreed that this behavioral finance drives their financial decisions. This is consistent with the findings by Pompian (2016) and van den Bergh-Lindeque et al. (2021). For the overconfidence bias, most of the sample (83.8%) also answered from the positive side of the spectrum, indicating that they somewhat agreed to strongly agreed that this behavioral finance drives their financial decisions. The minority of the sample (39%) recorded that they somewhat agreed to strongly agreed that anchoring drives their financial decisions. In comparison, most of the sample (65%) somewhat agreed to strongly agreed that the gambler’s fallacy influences their financial decisions. For the availability bias, most of the sample (86.1%) agreed that this bias influences their financial decisions. In relation, most respondents (66.5%) agreed that loss aversion drives their financial decisions. Similarly, more than 50% of the sample (60.4%) agreed that regret aversion influences financial decisions. In contrast, a minority (48.8%) of the respondents agreed that mental accounting drives their financial decisions. Lastly, the majority of the sample (91.4%) indicated that they agree that their financial decisions are influenced by self-control bias.

From Table 5, the self-control bias has the highest mean (mean = 4.78), indicating that this behavioral finance bias influences customers' financial decisions to the greatest extent, followed by the overconfidence bias (mean = 4.53), availability bias (mean = 4.38), loss aversion bias (mean = 4.06), representativeness bias (mean = 3.94), gambler fallacy bias (mean = 3.80), regret aversion bias (mean = 3.69), and mental accounting bias (mean = 3.36), which is also consistent with the studies by Ferriera (2018) and van den Bergh-Lindeque et al. (2021). Moreover, the anchoring bias had the lowest mean (mean = 3.10), indicating that bank customers' financial choices are influenced by this behavioral finance bias the least. However, responses to the statement in the mental accounting bias were more dispersed than in the other behavioral finance biases (Std. Dev. = 1.53).

<table>
<thead>
<tr>
<th>Table 5. Descriptive statistics for behavioral finance biases</th>
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<tbody>
<tr>
<td><strong>Behavioural finance bias</strong></td>
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<tr>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Representativeness</td>
</tr>
<tr>
<td>Overconfidence</td>
</tr>
<tr>
<td>Anchoring</td>
</tr>
<tr>
<td>Gambler fallacy</td>
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<tr>
<td>Availability bias</td>
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<tr>
<td>Loss aversion</td>
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<tr>
<td>Regret aversion</td>
</tr>
</tbody>
</table>
4.3. Correlation Analysis

Correlation analysis was also performed to determine whether customers’ behavioral biases affect their readiness for technology.

Table 6 reveals a statistically significant relationship between optimism and the following behavioral finance biases: overconfidence (p < 0.001) and gamblers fallacy (p < 0.001). The null hypothesis ($H_{01}$) may thus be rejected, and the alternative hypothesis ($H_{a1}$) can be concluded at a significance level of 5%. Furthermore, a weak positive, statistically significant relationship exists between optimism and the following biases: overconfidence ($r = 0.201$) and gambler’s fallacy ($r = 0.203$). In contrast, there was no statistically significant correlation between optimism and the following biases: representativeness ($p = 0.718$, $r = 0.019$), anchoring ($p = 0.883$, $r = -0.008$), availability bias ($p = 0.213$, $r = 0.067$), loss aversion ($p = 0.525$, $r = 0.034$), regret aversion ($p = 0.258$, $r = 0.061$), mental accounting ($p = 0.461$, $r = 0.04$) and self-control ($p = 0.716$, $r = 0.020$). The null hypothesis ($H_{01}$) may thus be concluded, and the alternative hypothesis ($H_{a1}$) can be rejected at a 5 per cent significance level.

<table>
<thead>
<tr>
<th>Behavioral finance biases</th>
<th>Spearman’s correlation</th>
<th>Optimism</th>
<th>Innovativeness</th>
<th>Insecurity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Representativeness</td>
<td>Coefficient (r)</td>
<td>0.019</td>
<td>0.032</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.718</td>
<td>0.553</td>
<td>0.466</td>
</tr>
<tr>
<td>Overconfidence</td>
<td>Coefficient (r)</td>
<td>0.201**</td>
<td>0.075</td>
<td>-0.150**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
<td>0.164</td>
<td>0.005</td>
</tr>
<tr>
<td>Anchoring</td>
<td>Coefficient (r)</td>
<td>-0.008</td>
<td>-0.165**</td>
<td>0.241**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.883</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td>Gambler’s fallacy</td>
<td>Coefficient (r)</td>
<td>0.203**</td>
<td>0.104</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.000</td>
<td>0.054</td>
<td>0.645</td>
</tr>
<tr>
<td>Availability bias</td>
<td>Coefficient (r)</td>
<td>0.067</td>
<td>0.062</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.213</td>
<td>0.247</td>
<td>0.975</td>
</tr>
<tr>
<td>Loss aversion</td>
<td>Coefficient (r)</td>
<td>0.034</td>
<td>-0.107*</td>
<td>0.182**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.525</td>
<td>0.047</td>
<td>0.001</td>
</tr>
<tr>
<td>Regret aversion</td>
<td>Coefficient (r)</td>
<td>0.061</td>
<td>-0.044</td>
<td>0.146**</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.258</td>
<td>0.412</td>
<td>0.006</td>
</tr>
<tr>
<td>Mental accounting</td>
<td>Coefficient (r)</td>
<td>0.040</td>
<td>-0.057</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.461</td>
<td>0.287</td>
<td>0.955</td>
</tr>
<tr>
<td>Self-control</td>
<td>Coefficient (r)</td>
<td>0.020</td>
<td>0.088</td>
<td>-0.129*</td>
</tr>
<tr>
<td></td>
<td>Sig. (2-tailed)</td>
<td>0.716</td>
<td>0.104</td>
<td>0.017</td>
</tr>
</tbody>
</table>

Notes: ** Correlation is significant at a 0.01 level (2-tailed); * Correlation is significant at a 0.01 level (2-tailed); N = 346

Regarding the relationship between behavioral finance biases and innovativeness, Table 6 demonstrates a statistically significant relationship between innovativeness and the following biases: anchoring ($p = 0.002$) and loss aversion ($p = 0.047$). At a five per cent significance level, the null hypothesis ($H_{02}$) may be rejected, and the alternative hypothesis ($H_{a2}$) can be accepted. However, a weak negative statistically significant relationship exists between innovativeness and the following biases: anchoring ($r = -0.165$) and loss aversion ($r = -0.107$). In contrast, there was no statistically significant relationship between innovativeness and the following biases: representativeness ($p = 0.553$, $r = 0.032$), overconfidence ($p = 0.164$, $r = 0.075$), gamblers fallacy ($p = 0.054$, $r = 0.104$), availability bias ($p = 0.247$, $r = 0.062$), regret aversion ($p = 0.412$, $r = -0.044$), mental accounting ($p = 0.287$, $r = -0.057$) and self-control ($p = 0.104$, $r = 0.088$). The null hypothesis ($H_{02}$) may thus be concluded, and the alternative hypothesis ($H_{a2}$) can be rejected at a 5% significance level.

Concerning the relationship between behavioral finance biases and insecurity, there is a statistically significant relationship between insecurity and the following biases: overconfidence ($p = 0.005$), anchoring ($p < 0.001$), loss aversion ($p = 0.001$), regret aversion ($p = 0.006$) and self-control ($p = 0.017$). The null hypothesis ($H_{03}$) may thus be rejected, while the alternative hypothesis ($H_{a3}$) can be concluded at a 5% significance level. However, a weak negative statistically significant relationship exists between insecurity and the following biases: overconfidence ($r = -0.150$) and self-control ($r = -0.129$). Conversely, a weak positive statistically significant relationship exists between insecurity and the following biases: anchoring ($r = 0.241$), loss aversion ($r = 0.182$), and regret aversion ($r = 0.146$). In contrast, there was no statistically significant relationship between insecurity and the following biases: representativeness ($p = 0.466$, $r = 0.039$), gamblers fallacy ($p = 0.645$, $r = -0.025$), availability bias ($p = 0.975$, $r = -0.002$) and mental accounting ($p = 0.955$, $r = 0.003$). The null hypothesis ($H_{03}$) may thus be accepted, and the alternative hypothesis ($H_{a3}$) can be rejected at a 5% significance level.

Based on the results mentioned above, overconfidence, anchoring, and loss aversion may be
deduced as the main biases influencing the adoption of new technology. The influence of overconfidence on technological readiness allows concluding that customers’ financial knowledge drives their adoption of new technology. The influence of anchoring on technological readiness may imply that customers rely predominantly on a specific quantity of information when deciding to adopt new technology. Furthermore, the influence of loss aversion on technological readiness may infer that customers are more inclined to avoid losses than to achieve gains when making decisions to adopt new technology. As discussed in the literature, Pompián (2012), Byrne and Utkus (2013), and Ferreira (2018) found that behavioral biases are important decision-making aspects. However, our study is among the first to investigate the influence of behavioral finance biases in the context of new technology adoption and more specifically AI adoption as proposed. Accordingly, the findings above are comparable with those by Tyebjee (1987), Chira et al. (2008), and van den Bergh-Lindeque et al. (2021), who studied behavioral biases in new products and behavioral finance from an investor perspective.

5. Conclusion

The developments in increased computational resources, growth of data, and reasoning models in the banking industry have made the field of AI and technology adoption captivating. Since South African banks operate in a highly competitive environment, the comprehension of technology adoption in this industry allows improving risk process efficiency and customer experience. Customer behavior plays an indispensable role in their decision-making. However, customer behaviours are also subjected to various factors, be they financial, psychological, or cognitive. The readiness of customers for technology and their behavioral biases are, consequently, some issues that affect the banking system and are subject to research. This study identified the behavioral biases that influence customers’ readiness for new technology. To achieve this objective, the researcher collected data from various customers, which were analyzed using various statistical analyses. In other words, descriptive statistics, including dispersion measures percentages, frequencies, and central tendency, were used to identify the behavioral biases influencing customers’ financial decisions.

The descriptive statistics showed that many customers indicated that a particular behavioral finance bias influences their financial decisions. Accordingly, it was determined that self-control bias has the most influence on the financial decisions of banking customers. The overconfidence bias, availability bias, loss aversion bias, representativeness bias, gambler fallacy bias, regret aversion bias, and mental accounting bias follow it. However, the anchoring bias slightly influences the financial decisions that customers of banks make. Most customers have stated that they disagree that this behavioral finance bias affects their financial choices.

Furthermore, a nonparametric Spearman’s rho correlation was also used to assess the relationship between behavioral finance biases and technological readiness dimensions. A weak positive, statistically significant relationship exists between optimism and the following biases: representativeness, anchoring, availability bias, loss aversion, regret aversion, mental accounting, and self-control. Moreover, a weak negative statistically significant relationship exists between innovativeness and the following biases: anchoring and loss aversion. In contrast, there is no statistically significant relationship between innovativeness and the following biases: representativeness, overconfidence, gambler fallacy, availability bias, regret aversion, mental accounting, and self-control. Conversely, a weak positive statistically significant relationship exists between insecurity and the following biases: overconfidence and self-control. Last, a weak negative statistically significant relationship exists between insecurity and the following biases: anchoring, loss aversion, and regret aversion. In contrast, there is no statistically significant relationship between insecurity and the following biases: representativeness, gambler fallacy, availability, and mental accounting.

It can be concluded that overconfidence, anchoring, and loss aversion may be deduced as the main biases influencing the adoption of new technology. The influence of overconfidence on technological readiness allows concluding that customers’ financial knowledge drives their adoption of new technology. In comparison, the influence of anchoring on technological readiness may imply that customers predominately depend on a single piece of information when deciding to adopt new technology. Furthermore, the influence of loss aversion on technological readiness may infer that customers are more inclined to avoid losses than to achieve gains when making decisions to adopt new technology.

Employing a comprehensive and accurate profiling of banking customers’ readiness to adopt AI banking products is essential as it provides South African banks and risk managers with improved insights and comprehension regarding the profile of customers who may be ready to adopt these new ways of intelligent banking. Therefore, this study contributes significantly to identifying behavioral biases that influence the adoption of AI technologies. However, there are limitations to any research project, which create new potential for future research efforts. The primary quantitative data for the study were obtained from 346 South African bank customers. Although this study met the sample adequacy recommended by previous researchers, future researchers can expand on the sample size considering the growing banking customer base banked by the South African banks. It is also recommended that future studies further segment the respondents by the type of banking account (e.g., savings, check, and private) to investigate the behavior
bias between the different types of customers. Furthermore, it is recommended that future research follow a mixed-methods approach by also incorporating qualitative interviews to examine the rationales as to why certain behavioral finance biases influence the adoption of AI.

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