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Behavioural Biases Influencing Technology Adoption by South African Bank Customers

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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

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摘要:
人工智能技术有潜力通过提供量身定制的产品和服务以及改善客户体验来加速金融业的转型。这种转型可以使南非的银行在市场和全球范围内获得竞争优势。本文旨在确定影响客户在银行内准备和采用创新技术的行为偏差。在实证主义范式下，使用非概率便利性和滚雪球抽样通过在线问卷收集数据。样本量包括南非的346家银行客户。通过因子分析（全民教育），研究发现客户表现出三个维度：乐观、创新和不安全感，将技术准备度描述为个人准备好接受新技术的一种心理状态。此外，通过描述性和相关性分析，研究结果表明，客户表现出过度自信、锚定和损失厌恶是影响银行内新技术采用的主要行为偏差。这项研究的实证结果至关重要，因为它们为南非银行和风险管理者提供了对可能准备采用人工智能银行产品的客户概况的更好的见解和理解。此外，建议未来的研究采用混合方法，同时纳入定性访谈，以检验某些行为金融学偏见影响人工智能采用而其他行为金融学偏见不影响人工智能采用的原因。

关键词：行为偏见、人工智能、技术、技术准备情况、南非。

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).

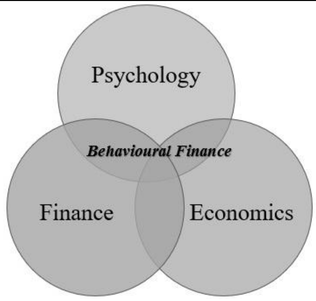

Figure 1. Components of financial decisions

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)

Bias	**Description**	**Authors**
Self-control	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.	Pompian (2012); O'Donoghue and Rabin (2015); Xiao and Porto (2019)
Loss aversion	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.	Tversky and Kahneman (1991); Byrne and Utkus (2013); Ferreira (2018)
Regret aversion	Regret is often characterized as a "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.	Jain et al. (2015)
Omission	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.	Ritov and Baron (1995); Kordes-de Vaal (1996)
Status quo	Emotional biases, such as the "status quo," 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.	Fleming et al. (2010); Pompian (2012)

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 2. Cognitive biases (Pompian & Wood, 2006; Thaler & Sunstein, 2008; Pompian, 2012; Byrne & Utkus, 2013; Jain et al., 2015; Sukumar & Metoyer, 2018; Ferreira, 2018)

Bias	**Description**	**Authors**
Overconfidence	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.	Lunn (2013); Jain et al. (2015); Virigineni and Rao (2017); Ferreira (2018)
Herding	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.	Thaler and Sunstein (2008); Jaiswal and Kamil (2012); Jain et al. (2015)
Hindsight	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.	Pompian (2012); Jain et al. (2015)
Cognitive dissonance	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.	Pompian (2012); Virigineni and Rao (2017); Sukumar and Metoyer (2018)
Anchoring	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.	Pompian and Wood (2006); Byrne and Utkus (2013); Sukumar and Metoyer (2018); Ferreira (2018)
Availability	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.	Byrne and Utkus (2013)
Rationalisation	Rationalisation occurs when individuals' proclivities for developing an acceptable rationale for prior actions boost their decision-making abilities.	Mazzoli and Marinelli (2011)
Representativeness:	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.	Jain et al. (2015)
Confirmation	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.	Pompian and Wood (2006); Sukumar and Metoyer (2018)

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 3. Dimensions of technological readiness (Parasuraman & Colby, 2015; Ramírez-Correa et al., 2020; Musyaffi et al., 2021)

Dimensions	**Definitions**	**Authors**
Optimism	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.	Parasuraman and Colby (2015); Musyaffi et al. (2021)
Innovativeness	Innovativeness is a natural inclination toward experimenting with innovation. Additionally, innovativeness is a facilitator in determining technological readiness.	Ramírez-Correa et al. (2020); Amer and Atheer (2022)
Discomfort	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.	Parasuraman and Colby (2015); Berndt et al. (2010); Ramírez-Correa et al. (2020)
Insecurity	Insecurity refers to skepticism about technology and doubts about its capacity to function correctly. Insecurity also serves as an inhibitor to technological readiness.	Parasuraman and Colby (2015); Musyaffi et al. (2021); Amer and Atheer (2022)

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; Yussaivi 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_{02}: There is no association between behavioral finance biases and innovativeness.

H_{a2}: There is an association between behavioral finance biases and innovativeness.

H_{03}: There is no association between behavioral finance biases and insecurity.

H_{a3}: There is an 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

Item	**Factors**		
	Optimism	**Innovativeness**	**Insecurity**
I use e-wallets and instant money when sending money to someone	0.779		
I use my bank app to purchase airtime, electricity, data, etc.	0.651		
I use non-contact payment options when paying for goods or services	0.587		
I use online tools(internet banking, bank app) to apply for bank products (personal loans, credit card limit increase)	0.543		
I use my bank app to make online payments (utility, account, etc.)	0.520		
I use my fingerprint detection to open my bank app	0.474		
I will use online communication platforms (Twitter, WhatsApp) to communicate with my bank		0.795	
I am willing to use contactless payment options (Zapper, Snapscan etc.) to settle bills		0.757	
I am open to using intelligent robots (chatbots) as financial advisors and tellers.		0.748	
I am willing to use paperless banking to apply for bank products (loans, credit cards, vehicle finance etc.)		0.707	
I am ready to use facial recognition and fingerprint detection as personal identification tools for banking		0.666	
I use the ATM to get my statements			0.787

Continuation of Table 4			
I go to the branch to do my banking			0.688
I use physical cash when paying for items			0.633
I use consultants on the banking floor rather than self-service machines			0.580
Eigenvalue	4.627	1.766	1.459
% of Variance	30.844	11.776	9.728
Cumulative %	30.844	42.620	52.348

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 5. Descriptive statistics for behavioral finance biases

Behavioural finance bias	**Item**	**N**	**Minimum**	**Maximum**	**Mean**	**Standard deviation**
Representativeness	D1	346	1.00	6.00	3.94	1.35
Overconfidence	D2	346	1.00	6.00	4.53	1.19
Anchoring	D3	346	1.00	6.00	3.10	1.41
Gambler fallacy	D4	346	1.00	6.00	3.80	1.29
Availability bias	D5	346	1.00	6.00	4.38	1.04
Loss aversion	D6	346	1.00	6.00	4.06	1.46
Regret aversion	D7	346	1.00	6.00	3.69	1.55

Continuation of Table 5

Mental accounting	D8	346	1.00	6.00	3.36	1.56
Self-control	D9	346	1.00	6.00	4.78	1.02

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 behavioural 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 6. Association between behavioral finance biases and technological readiness

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

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-percent 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, Pompian (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: overconfidence and gambler's fallacy. In contrast, no statistically significant correlation existed 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. Last, a weak negative statistically significant relationship exists between insecurity and the following biases: overconfidence and self-control. Conversely, a weak positive 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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References

[1] AMEEN, N., TARHINI, A., & ANAND, A. (2021). Customer experience in the age of artificial intelligence. *Computers in Human Behavior*, 114, 106548. https://doi.org/10.1016/j.chb.2020.106548

[2] AMER, M.J., & ATHEER, A.M. (2022). The Impact of Management with Intelligence on Technological Readiness: Field Research in Iraqi Telecom Companies. *International Journal of Research in Social Sciences & Humanities*, 12(4), 138-149. http://doi.org/10.37648/ijrssh.v12i04.009

[3] ASMAH, A.E., OFOEDA, J., & GYAPONG, K. (2018). Understanding the electronic cheque clearing system in Ghana. *Electronic Journal of Information Systems Evaluation*, 21(1), 20-34. Retrieved from https://academic-publishing.org/index.php/ejise/article/view/139

[4] BELANCHE, D., CASALÓ, L.V., & FLAVIÁN, C. (2019). Artificial intelligence in fintech: Understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, 119(7), 1411-1430. https://doi.org/10.1108/IMDS-08-2018-0368

[5] BERNDT, A., SAUNDERS, S., & PETZER, D.J. (2010). Readiness for banking technologies in developing countries. *Southern African Business Review*, 14(3), 47-76. Retrieved from https://www.unisa.ac.za/static/corporate_web/Content/Colleges/CEMS/Schools,%20departments,%20bureau,%20centres%20&%20institute/SA%20Business%20Review/documents/SABVIEW14_3_chap_3.pdf

[6] BYRNE, B.A., & UTKUS, W.S.P. (2013). *Behavioural Finance. Understanding How the Mind Can Help or Hinder Investment Success.* The Vanguard Group.

[7] CHIRA, I., ADAMS, M., & THORNTON, B. (2008). Behavioral Bias within the Decision Making Process. *Journal of Business and Economics Research*, 6(8), 11-20. https://doi.org/10.19030/jber.v6i8.2456

[8] CRESWELL, J.W. (2014). *Research design: qualitative, quantitative and mixed methods approaches*. 4th ed. Thousand Oaks, California: SAGE.

[9] DAVIES, H., & GREEN, D. (2010). *Banking on the Future: The Fall and Rise of Central Banking*. Princeton, New Jersey: Princeton University Press.

[10] DIVANNA, J.A. (2003). *The future of retail banking*. London: Palgrave Macmillan.

[11] DOUGLES, J. (2018). *Manufacturing Debt: A History of the Bank Credit Card Infrastructure*. Ph.D. dissertation, University of Toronto.

[12] EDVARDSSON, B., & ROOS, I. (2003). Customer complaints and switching behaviour—a study of relationship dynamics in a telecommunication company. *Journal of Relationship Marketing*, 2(1-2), 43-68. https://doi.org/10.1300/J366v02n01_04

[13] FAKHRY, B. (2016). A literature review of behavioural finance. *Journal of Economics Library*, 3(3), 458-465. http://dx.doi.org/10.1453/jel.v3i3.929

[14] FERREIRA, S.J. (2018). *Reputational risk: depositor behaviour in South Africa*. Ph.D. dissertation, North-West University.

[15] FLEMING, S.M., THOMAS, C.L., & DOLAN, R.J. (2010). Overcoming status quo bias in the human brain. *Proceedings of the National Academy of Sciences*, 107(13), 6005-6009. https://doi.org/10.1073/pnas.0910380107

[16] GLASER, F., ILIEWA, Z., JUNG, D., & WEBER, M. (2019). Towards Designing Robo-advisors for Unexperienced Investors with Experience Sampling of Time-Series Data. In: DAVIS, F., RIEDL, R., VOM BROCKE, J., LÉGER, P.M., & RANDOLPH, A. (eds.) *Information Systems and Neuroscience. Lecture Notes in Information Systems and Organisation*, Vol. 29. Cham: Springer, pp. 133-138. https://doi.org/10.1007/978-3-030-01087-4_16

[17] GRAVETTER, F.J., WALLNAU, L.B., FORZANO, L.A.B., & WITNAUER, J.E. (2020). *Essentials of statistics for the behavioral sciences.* Cengage Learning.

[18] GUPTA, V.S., & GARG, R. (2015). Technology readiness index of e-banking users: Some measurement and sample survey evidence. *The IUP Journal of Bank Management*, 14(4), 43-58.

[19] HAMMOND, K. (2015). *Practical artificial intelligence for dummies*. New York: John Wiley & Sons.

[20] 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), a602. https://doi.org/10.4102/jef.v14i1.602

[21] ILLIA, A., NGNIATEDEMA, T., & HUANG, Z. (2015). A conceptual model for mobile banking adoption. *Journal of Management Information & Decision Sciences*, 18(1), 111-122. Retrieved from https://www.abacademies.org/articles/aimsjvol18no12015.pdf

[22] JAIN, R., JAIN, P., & JAIN, C. (2015). Behavioral biases in the decision making of individual investors. *The IUP Journal of Management Research*, 14(3), 7-27. Retrieved from https://ssrn.com/abstract=2692415

[23] JAISWAL, B., & KAMIL, N. (2012). Gender,

behavioral finance and the investment decision. *Business Review*, 7(2), 8-22. https://doi.org/10.54784/1990-6587.1201

[24] JUBRAJ, R., GRAHAM, T., & RYAN, E. (2018). *Redefine banking with artificial intelligence*. Retrieved from https://www.accenture.com/gb-en/insight-ai-redefine-banking#zoom=50

[25] JUDD, E. (2017). Timeline: 180 years of banking technology. *Independent Banker*. Retrieved from https://www.independentbanker.org/article/2017/11/01/timeline-180-years-of-banking-technology

[26] KHALID, K., HILMAN, H., & KUMAR, D. (2012). Get along with quantitative research process. *International Journal of Research in Management*, 2(2), 15-29. Retrieved from https://repo.uum.edu.my/id/eprint/7187/

[27] KHAN, A.P., KHAN, S., & XIANG, I.A.R. (2017). Factors influencing consumer intentions to adopt online banking in Malaysia. *Business & Economic Review*, 9(2), 101-134. https://dx.doi.org/10.22547/BER/9.2.5

[28] 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. https://doi.org/10.1002/asi.22987

[29] KIM, K.-H. (2012). Emotion and strategic decision-making behavior: Developing a theoretical model. *International Journal of Business and Social Science*, 3(1), 105-113. Retrieved from http://ijbssnet.com/view.php?u=http://ijbssnet.com/journals/Vol_3_No_1_January_2012/11.pdf

[30] KORDES-DE VAAL, J.H. (1996). Intention and the omission bias: Omissions perceived as nondecisions. *Acta Psychologica*, 93(1-3), 161-172. https://doi.org/10.1016/0001-6918(96)00027-3

[31] 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. https://doi.org/10.1016/j.socec.2011.04.008

[32] KURZWEIL, R., RICHTER, R., KURZWEIL, R., & SCHNEIDER, M. (1990). *The age of intelligent machines*. Cambridge, Massachusetts: The MIT Press.

[33] LUNN, P.D. (2013). The role of decision-making biases in Ireland's banking crisis. *Irish Political Studies*, 28(4), 563-590. https://doi.org/10.1080/07907184.2012.742068

[34] MAZZOLI, C., & MARINELLI, N. (2011). The Role of Risk in the Investment Decision Process: Traditional vs Behavioural Finance. In: LUCARELLI, C., & BRIGHETTI, G. (eds.) *Risk Tolerance in Financial Decision Making. Palgrave Macmillan Studies in Banking and Financial Institutions.* London: Palgrave Macmillan, pp. 8–66. https://doi.org/10.1057/9780230303829_2

[35] MCDANIEL, J.C., & GATES, R. (2018). *Marketing research*. 11th ed. Hoboken, New Jersey: John Wiley & Sons.

[36] MELAS, C.D., ZAMPETAKIS, L.A., DIMOPOULOU, A., & MOUSTAKIS, V.S. (2014). An empirical investigation of technology readiness among medical staff based in Greek hospitals. *European Journal of Information Systems*, 23(6), 672-690. https://doi.org/10.17010/pijom/2015/v8i11/81252

[37] 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. https://doi.org/10.1016/j.eswa.2014.09.024

[38] MURADOGLU, G., & HARVEY, N. (2012). Behavioural finance: The role of psychological factors in financial decisions. *Review of Behavioural Finance*, 4(2), 68-80. https://doi.org/10.1108/19405971211284862

[39] 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(Special Issue 4), 1-18. Retrieved from https://www.abacademies.org/articles/lack-of-readiness-of-digital-banking-channel-acceptance-study-on-tam-3-and-technology-readiness.pdf

[40] O'DONOGHUE, T., & RABIN, M. (2015). Present bias: Lessons learned and to be learned. *American Economic Review*, 105(5), 273-279. http://dx.doi.org/10.1257/aer.p20151085

[41] ODUSINA, A.O. (2014). Automated teller machine usage and customers satisfaction in Nigeria. *Global Journal of Management and Business Research*, 2(3), 43-47.

[42] PALLANT, J. (2013). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS*. 5th ed. London: Routledge. https://doi.org/10.4324/9781003117445

[43] PARASURAMAN, A., & COLBY, C.L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, 18(1), 59-74. https://doi.org/10.1177/1094670514539730

[44] PARK, J.Y., RYU, J.P., & SHIN, H.J. (2016). Robo-advisors for portfolio management. *Advanced Science and Technology Letters*, 141(1), 104-108.

[45] PARKINSON, B., TOTTERDELL, P., BRINER, R.B., & REYNOLDS, S. (1996). *Changing moods: The psychology of mood and mood regulation*. London: Longman.

[46] POMPIAN, M.M. (2012). *Behavioral finance and investor types: managing behavior to make better investment decisions.* New York: John Wiley & Sons.

[47] POMPIAN, M.M. (2016). Risk profiling through a behavioral finance lens. *Research Foundation Briefs*, 2(1), 1-26.

[48] 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.
[49] QUINLAN, C., BABIN, B., CARR, J., GRIFFIN, M., & ZIKMUND, W.G. (2015). *Business research methods*. Hampshire: Cengage Learning.
[50] RAMÍREZ-CORREA, P., GRANDÓN, E., & RONDÁN-CATALUÑA, J. (2020). Users segmentation based on the technological readiness adoption index in emerging countries: The case of Chile. *Technological Forecasting and Social Change*, 155, 120035. https://doi.org/10.1016/j.techfore.2020.120035
[51] RICCIARDI, V. (2008). The psychology of risk: the behavioral finance perspective. In: FABOZZI, F.J. (ed.) *Handbook of finance: investment management and financial management*. 2nd ed. New York: John Wiley & Sons, pp. 85-112. http://dx.doi.org/10.1002/9780470404324.hof002010
[52] RITOV, I., & BARON, J. (1995). Outcome knowledge, regret, and omission bias. *Organisational Behavior and Human Decision Processes*, 64(2), 119-127. http://dx.doi.org/10.1006/obhd.1995.1094
[53] ROSSINI, L., & MAREE, J. (2010). *Business management for financial planners: A guide to creating a sustainable service-based financial planning business*. Claremont, California: Juta and Company Ltd.
[54] 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. https://doi.org/10.1108/JRIM-01-2016-0005
[55] SARSTEDT, M., & MOOI, E. (2019). *A Concise Guide to Market Research: The Process, Data, and Methods Using IBM SPSS Statistics*. 3rd ed. Berlin: Springer. https://doi.org/10.1007/978-3-662-56707-4
[56] SEKARAN, U., & BOUGIE, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.
[57] 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 & Marketing*, 32(8), 860-873. https://doi.org/10.1002/mar.20823
[58] SREEDEVI, V. (2013). E-Banking and Cheque Truncation System (CTS). *Indian Journal of Applied Research*, 3(2), 184-186. Retrieved from https://www.worldwidejournals.com/indian-journal-of-applied-research-(IJAR)/fileview/February_2013_1359812945_55158_64.pdf
[59] SUBASH, R. (2012). *Role of behavioral finance in portfolio investment decisions: Evidence from India*. Master's dissertation, Charles University in Prague. Retrieved from https://dspace.cuni.cz/bitstream/handle/20.500.11956/43150/DPTX_2010_2__0_332599_0_110165.pdf?sequence=1
[60] SUKUMAR, P.T., & METOYER, R. (2018). A visualisation approach to addressing reviewer bias in holistic college admissions. In: ELLIS, G. (ed.) *Cognitive biases in visualisations*. Cham: Springer, pp. 161-175. https://doi.org/10.1007/978-3-319-95831-6_12
[61] TAKEMURA, K. (2014). *Behavioral decision theory: Psychological and mathematical descriptions of human choice behavior*. Tokyo: Springer. https://doi.org/10.1007/978-4-431-54580-4
[62] THALER, R.H., & SUNSTEIN, C.R. (2008). Nudge: Improving decisions about health. *Wealth, and Happiness*, 6, 14-38.
[63] TSAI, H.-F., CHANG, B.R., HUANG, H.-C., & HUANG, C.-F. (2019). Implementation of mobile point of sale cashier management system. *Sensors and Materials*, 31(8), 2463-2476. https://doi.org/10.18494/SAM.2019.2427
[64] TVERSKY, A., & KAHNEMAN, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, 106(4), 1039-1061. https://doi.org/10.2307/2937956
[65] TYEBJEE, T.T. (1987). Behavioral biases in new product forecasting. *International Journal of Forecasting*, 3(3-4), 393-404. https://doi.org/10.1016/0169-2070%2887%2990032-X
[66] VAN DEN BERGH-LINDEQUE, A. (2021). *The influence of endogenous and exogenous factors on investor risk-tolerance behaviour*. Ph.D. dissertation, North-West University. Retrieved from https://repository.nwu.ac.za/handle/10394/37052
[67] VAN DEN BERGH-LINDEQUE, A., FERREIRA-SCHENK, S., & DICKASON-KOEKEMOER, Z. (2021). Individual Investor Risk Tolerance from a Behavioural Finance Perspective in Gauteng, South Africa. *International Journal of Economics and Financial Issues*, 11(4), 53–65. https://doi.org/10.32479/ijefi.11451
[68] VAN DYK, R., & VAN BELLE, J.-P. (2019). Factors influencing the intended adoption of digital transformation: A South African case study. Proceedings of the Federated Conference on Computer Science and Information Systems, Leipzig, 1-4 September 2019, pp. 519-528. https://doi.org/10.15439/2019F166
[69] VIRIGINENI, M., & RAO, M.B. (2017). Contemporary developments in behavioural finance. *International Journal of Economics and Financial Issues*, 7(1), 448-459. Retrieved from https://econjournals.com/index.php/ijefi/article/view/3809
[70] WATT, B. (2017). *The rise of mPOS: How*

mobile point-of-sale is transforming the hospitality industry. Retrieved from https://www.paycorp.co.za/rise-mpos-mobile-point-sale-transforming-hospitality-industry

[71] XIAO, J.J., & PORTO, N. (2019). Present bias and financial behavior. *Financial Planning Review*, 2(2), e1048. https://doi.org/10.1002/cfp2.1048

[72] YAO, M., ZHOU, A., & JIA, M. (2018). *Applied artificial intelligence: A handbook for business leaders*. New York: Topbots.

[73] YUSSAIVI, A., LU, C., SYARIEF, M., & SUHARTANTO, D. (2021). The Use of Contemporary Mobile Banking Service in Islamic Banks: Perspective of Young Customers. *International Journal of Applied Business Research*, 3(1), 39-53. https://doi.org/10.35313/ijabr.v3i1.121

参考文:

[1] AMEEN, N.、TARHINI, A. 和 ANAND, A. (2021)。人工智能时代的客户体验。计算机在人类行为中的应用， 114, 106548。https://doi.org/10.1016/j.chb.2020.106548

[2] AMER, M.J., & ATHEER, A.M.（2022）。情报管理对技术准备的影响：伊拉克电信公司的实地研究。国际社会科学与人文研究杂志， 12(4), 138-149。http://doi.org/10.37648/ijrssh.v12i04.009

[3] ASMAH, A.E.、OFOEDA, J. 和 GYAPONG, K. (2018)。了解加纳的电子支票清算系统。信息系统评估电子杂志， 21(1), 20-34。检索自https://academic-publishing.org/index.php/ejise/article/view/139

[4] BELANCHE, D.、CASALÓ, L.V. 和 FLAVIÁN, C. (2019)。金融科技中的人工智能：了解客户对机器人顾问的采用情况。工业管理与数据系统，119(7), 1411-1430。https://doi.org/10.1108/IMDS-08-2018-0368

[5] 伯恩特, A., 桑德斯, S., &佩泽，D.J.（2010）。发展中国家对银行技术的准备情况。南部非洲商业评论， 14(3), 47-76。摘自https://www.unisa.ac.za/static/corporate_web/Content/Colleges/CEMS/Schools,%20departments,%20bureau,%20centres%20&%20institute/SA%20Business%20Review/documents/SABVIEW14_3_chap_3.pdf

[6] BYRNE, B.A., & UTKUS, W.S.P.（2013）。行为金融学。了解思维如何帮助或阻碍投资成功。先锋集团。

[7] I. 奇拉、M. 亚当斯和 B. 桑顿 (2008)。决策过程中的行为偏差。商业与经济研究杂志， 6(8), 11-20。https://doi.org/10.19030/jber.v6i8.2456

[8]克雷斯威尔, J.W.（2014）。研究设计：定性、定量和混合方法。第四版。加利福尼亚州千橡市：智者。

[9]戴维斯，H., &格林, D.（2010）。未来银行业：中央银行业的衰落与崛起。新泽西州普林斯顿：普林斯顿大学出版社。

[10]迪瓦娜, J.A.（2003）。零售银行业务的未来。伦敦：帕尔格雷夫·麦克米伦。

[11]道格斯, J.（2018）。制造业债务：银行信用卡基础设施的历史。博士 论文，多伦多大学。

[12] EDVARDSSON, B. 和 ROOS, I. (2003)。客户投诉和转换行为——电信公司关系动态研究。关系营销杂志，2(1-2), 43-68。https://doi.org/10.1300/J366v02n01_04

[13]FAKHRY, B.（2016）。行为金融学文献综述。经济学杂志图书馆， 3(3), 458-465。http://dx.doi.org/10.1453/jel.v3i3.929

[14]费雷拉，S.J.（2018）。声誉风险：南非的储户行为。博士 论文，西北大学。

[15]弗莱明, S.M., 托马斯，C.L., 和多兰，R.J.（2010）。克服人脑的现状偏见。美国国家科学院院刊, 107(13), 6005-6009。https://doi.org/10.1073/pnas.0910380107

[16] GLASER, F.、ILIEWA, Z.、JUNG, D. 和 WEBER, M. (2019)。通过时间序列数据的经验采样为缺乏经验的投资者设计机器人顾问。见：DAVIS, F.、RIEDL, R.、VOM BROCKE, J.、LÉGER, P.M. 和 RANDOLPH, A.（编辑）信息系统和神经科学。信息系统和组织讲义，卷。29. 詹：施普林格, 第 133-138 页。https://doi.org/10.1007/978-3-030-01087-4_16

[17] GRAVETTER, F.J.、WALLNAU, L.B.、FORZANO, L.A.B. 和 WITNAUER, J.E. (2020)。行为科学统计学要点。圣智学习。

[18] GUPTA, V.S. 和 GARG, R. (2015)。电子银行用户的技术准备度指数：一些测量和抽样调查证据。《子宫内膜异位症银行管理杂志》，14(4), 43-58。

[19]哈蒙德, K.（2015）。面向傻瓜的实用人工智能。纽约：约翰·威利父子公司。

[20] HYLAND, L.、SEBASTIAN, A. 和 SEETHARAM, Y. (2021)。行为金融学在银行业的应用：发现银行案例。经济与金融科学杂志，14(1), a602。https://doi.org/10.4102/jef.v14i1.602

[21] ILLIA, A.、NGNIATEDEMA, T. 和 HUANG, Z. (2015)。移动银行采用的概念模型。管理信息与决策科学杂志， 18(1), 111-122。摘自https://www.abacademies.org/articles/aimsjvol18no12015.pdf

[22] JAIN, R.、JAIN, P. 和 JAIN, C. (2015)。个人投资者决策中的行为偏差。子宫内

膜异位症管理研究杂志， 14(3), 7-27。检索自https://ssrn.com/abstract=2692415
[23] JAISWAL, B. 和 KAMIL, N. (2012)。性别、行为金融学和投资决策。商业评论， 7(2), 8-22。https://doi.org/10.54784/1990-6587.1201
[24] JUBRAJ, R.、GRAHAM, T. 和 RYAN, E. (2018)。用人工智能重新定义银行业。摘自https://www.accenture.com/gb-en/insight-ai-redefine-banking#zoom=50
[25]贾德，E.（2017）。时间表：银行技术180年。独立银行家。摘自https://www.independentbanker.org/article/2017/11/01/timeline-180-years-of-banking-technology
[26] 哈立德 K.、希尔曼 H. 和库马尔 D. (2012)。适应定量研究过程。国际管理研究杂志， 2(2), 15-29。检索自https://repo.uum.edu.my/id/eprint/7187/
[27] KHAN, A.P.、KHAN, S. 和 XIANG, I.A.R.（2017）。影响马来西亚消费者采用网上银行意愿的因素。商业与经济评论， 9(2), 101-134。https://dx.doi.org/10.22547/BER/9.2.5
[28] KIM, D., CHUN, H., & LEE, H. (2014)。确定影响大学生采用智能手机的因素。信息科学技术协会学报， 65(3), 578-588。https://doi.org/10.1002/asi.22987
[29] KIM，K.-H。（2012）。情感和战略决策行为：开发理论模型。国际商业与社会科学杂志， 3(1), 105-113。摘自http://ijbssnet.com/view.php?u=http://ijbssnet.com/journals/Vol_3_No_1_January_2012/11.pdf
[30] 科德斯-德瓦尔，J.H.（1996）。意图和遗漏偏差：遗漏被视为不做决定。心理学报， 93（1-3），161-172。https://doi.org/10.1016/0001-6918(96)00027-3
[31] KOURTIDIS, D.、ŠEVIĆ, Ž. 和 CHATZOGLOU, P. (2011)。投资者的交易活动：行为视角和实证结果。社会经济学杂志， 40(5), 548-557。https://doi.org/10.1016/j.socec.2011.04.008
[32] KURZWEIL，R.、RICHTER，R.、KURZWEIL，R. 和 SCHNEIDER, M. (1990)。智能机器时代。马萨诸塞州剑桥：麻省理工学院出版社。
[33]伦恩，P.D.（2013）。决策偏差在爱尔兰银行业危机中的作用。爱尔兰政治研究， 28(4), 563-590。https://doi.org/10.1080/07907184.2012.742068
[34] MAZZOLI, C. 和马里内利, N. (2011)。风险在投资决策过程中的作用：传统金融与行为金融。见：LUCARELLI, C. 和 BRIGHETTI, G.（编辑）财务决策中的风险容忍度。帕尔格雷夫·麦克米伦银行和金融机构研究。伦敦：帕尔格雷夫·麦克米伦，第 8-66 页。https://doi.org/10.1057/9780230303829_2
[35]麦克丹尼尔，J.C.和盖茨，R.（2018）。市场研究。第11版。新泽西州霍博肯：约翰·威利父子公司。
[36] MELAS, C.D.、ZAMPETAKIS, L.A.、DIMOPOULOU, A. 和 MOUSTAKIS, V.S.（2014）。对希腊医院医务人员技术准备情况的实证调查。欧洲信息系统杂志，23(6), 672-690。https://doi.org/10.17010/pijom/2015/v8i11/81252
[37] MORO, S.、CORTEZ, P. 和 RITA, P. (2015)。银行业商业智能：2002年至2013年使用文本挖掘和潜在狄利克雷分配的文献分析。专家系统与应用， 42(3), 1314-1324。https://doi.org/10.1016/j.eswa.2014.09.024
[38] MURADOGLU, G. 和 HARVEY, N. (2012)。行为金融学：心理因素在金融决策中的作用。行为金融学评论， 4(2), 68-80。https://doi.org/10.1108/19405971211284862
[39] MUSYAFFI, A.M.、MULYANI, S.、SURAIDA, I. 和 SUKMADILAGA, C. (2021)。数字银行渠道接受度准备不足：塔姆3和技术准备度研究。战略管理学会学报，20（特刊 4）， 1-18。摘自https://www.abacademies.org/articles/lack-of-readiness-of-digital-banking-channel-acceptance-study-on-tam-3-and-technology-readiness.pdf
[40] O'DONOGHUE, T. 和 RABIN, M. (2015)。当前偏见：吸取的教训和需要吸取的教训。《美国经济评论》， 105(5), 273-279。http://dx.doi.org/10.1257/aer.p20151085
[41]奥杜西娜，A.O.（2014）。尼日利亚自动柜员机的使用情况和客户满意度。全球管理与商业研究杂志，2(3), 43-47。
[42]帕兰特，J.（2013）。统计软件生存手册：使用国际商业机器公司统计软件进行数据分析的分步指南。第五版。伦敦：劳特利奇。https://doi.org/10.4324/9781003117445
[43] PARASURAMAN, A. 和 COLBY, C.L.（2015）。更新和简化的技术准备指数：TRI 2.0。服务研究杂志， 18(1), 59-74。https://doi.org/10.1177/1094670514539730
[44] PARK, J.Y., RYU, J.P., & SHIN, H.J. (2016)。用于投资组合管理的机器人顾问。高级科学技术快报，141(1), 104-108。
[45]帕金森，B.，托特戴尔，P.，布林纳，R.B.，& 雷诺兹，S.

(1996)。改变情绪：情绪心理学和情绪调节。伦敦：朗文。

[46]庞皮安，M.M.（2012）。行为金融学和投资者类型：管理行为以做出更好的投资决策。纽约：约翰·威利父子公司。

[47]庞皮安，M.M.（2016）。通过行为金融学视角进行风险分析。研究基金会简介， 2(1), 1-26。

[48] 庞皮安，M.M., & 伍德, A.S.（2006）。行为金融和财富管理：如何为私人客户建立最佳投资组合。新泽西州：约翰·威利父子公司。

[49] QUINLAN, C.、BABIN, B.、CARR, J.、GRIFFIN, M. 和 ZIKMUND, W.G. (2015)。商业研究方法。汉普郡：参与学习。

[50] RAMÍREZ-CORREA, P.、GRANDÓN, E. 和 RONDÁN-CATALUÑA, J. (2020)。新兴国家基于技术成熟度采用指数的用户细分：以智利为例。技术预测和社会变革，155, 120035。https://doi.org/10.1016/j.techfore.2020.120035

[51]里恰尔迪, V.（2008）。风险心理学：行为金融学观点。见：FABOZZI, F.J.（主编）《金融手册：投资管理和财务管理》。第二版。纽约：约翰·威利父子公司, 第 85-112 页。http://dx.doi.org/10.1002/9780470404324.hof002010

[52] RITOV, I., & BARON, J. (1995)。结果知识、遗憾和遗漏偏差。组织行为和人类决策过程， 64(2), 119-127。http://dx.doi.org/10.1006/obhd.1995.1094

[53]罗西尼，L., &玛丽，J.（2010）。财务规划师的业务管理：创建基于服务的可持续财务规划业务的指南。加利福尼亚州克莱蒙特：巨塔有限公司.

[54]罗伊，S., &穆尔蒂, Y.（2017）。技术准备度、感知无处不在和移动商务采用：隐私的调节作用。互动营销研究杂志， 11(3), 268-295。https://doi.org/10.1108/JRIM-01-2016-0005

[55] SARSTEDT, M., & MOOI, E. (2019)。市场研究简明指南：使用国际商业机器公司统计软件统计的流程、数据和方法。第三版。柏林：施普林格。https://doi.org/10.1007/978-3-662-56707-4

[56] SEKARAN, U. 和 BOUGIE, R. (2016)。商业研究方法：技能培养方法。约翰·威利父子。

[57] SLADE, E.L.、DWIVEDI, Y.K.、PIERCY, N.C. 和 WILLIAMS, M.D. (2015)。对英国消费者采用远程移动支付的意图进行建模：通过创新、风险和信任扩展UTAUT。心理学与营销， 32(8), 860-873。https://doi.org/10.1002/mar.20823

[58] SREEDEVI, V. (2013)。电子银行和支票截断系统（CTS）。印度应用研究杂志， 3(2), 184-186。摘自https://www.worldwidejournals.com/indian-journal-of-applied-research-(IJAR)/fileview/February_2013_1359812945_5515864.pdf

[59] SUBASH, R. (2012)。行为金融学在投资组合决策中的作用：来自印度的证据。硕士学位论文，布拉格查尔斯大学。检索自https://dspace.cuni.cz/bitstream/handle/20.500.11956/43150/DPTX_2010_2__0_332599_0_110165.pdf?sequence=1

[60] SUKUMAR, P.T. 和 METOYER, R. (2018)。解决整体大学招生中审稿人偏见的可视化方法。见：ELLIS, G.（编辑）可视化中的认知偏差。詹：施普林格，第 161-175 页。https://doi.org/10.1007/978-3-319-95831-6_12

[61] 竹村 K. (2014)。行为决策理论：人类选择行为的心理学和数学描述。东京：施普林格。https://doi.org/10.1007/978-4-431-54580-4

[62] THALER, R.H., & SUNSTEIN, C.R. (2008)。助推：改善有关健康的决策。财富与幸福，6, 14-38。

[63]蔡宏峰、张博瑞、黄宏昌、黄宏峰。（2019）。实施移动销售点收银管理系统。传感器和材料，31(8), 2463-2476。https://doi.org/10.18494/SAM.2019.2427

[64] TVERSKY, A. 和 KAHNEMAN, D. (1991)。无风险选择中的损失厌恶：参考依赖模型。经济学季刊， 106(4), 1039-1061。https://doi.org/10.2307/2937956

[65] TYEBJEE, T.T. (1987)。新产品预测中的行为偏差。国际预测杂志， 3(3-4), 393-404。https://doi.org/10.1016/0169-2070%2887%2990032-X

[66] 范登伯格-林德克, A.（2021）。内生和外生因素对投资者风险承受行为的影响。博士论文，西北大学。检索自https://repository.nwu.ac.za/handle/10394/37052

[67] VAN DEN BERGH-LINDEQUE, A.、FERREIRA-SCHENK, S. 和 DICKASON-KOEKEMOER, Z. (2021)。南非豪登省行为金融学角度的个人投资者风险承受能力。国际经济与金融问题杂志，11(4), 53–65。https://doi.org/10.32479/ijefi.11451

[68] VAN DYK, R. 和 VAN BELLE, J.-P。（2019）。影响数字化转型预期采用的因素：南非案例研究。计算机科学与信息系统联合会

会议记录，莱比锡，2019年9月1-4日，第 519-528 页。https://doi.org/10.15439/2019F166

[69] VIRIGINENI, M., & RAO, M.B.（2017）。行为金融学的当代发展。国际经济与金融问题杂志， 7(1), 448-459。检索自https://econjournals.com/index.php/ijefi/article/view/3809

[70]瓦特，B.（2017）。移动销售点的兴起：移动销售点如何改变酒店业。检索自https://www.paycorp.co.za/rise-mpos-mobile-point-sale-transforming-hospitality-industry

[71] 肖建军，&波尔图，N. (2019)。目前的偏见和财务行为。财务规划审查，2(2), e1048。https://doi.org/10.1002/cfp2.1048

[72]姚明、周爱、贾明（2018）。应用人工智能：商业领袖手册。纽约：顶级机器人。

[73] YUSSAIVI, A.、LU, C.、SYARIEF, M. 和 SUHARTANTO, D. (2021)。伊斯兰银行现代移动银行服务的使用：年轻客户的视角。国际应用商业研究杂志，3(1), 39-53。https://doi.org/10.35313/ijabr.v3i1.121