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CUSTOMER ENGAGEMENT AND DATA-DRIVEN CUSTOMISATION IN THE RETAIL BANKING SECTOR IN SOUTH AFRICA

by

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A research report submitted in partial fulfilment of the requirements for the degree of

MASTER OF BUSINESS ADMINISTRATION

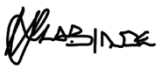
in the
Faculty of Commerce, Law and Management
University of Witwatersrand

Supervisor: Dr Yvonne Kabeya Saini

June 2025

DECLARATION

I, Mabel Thandiwe Nkabinde, declare that this research article is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the Graduate School of Business Administration, University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Signature:  **Date: 30 June 2025**

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ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to everyone who supported me throughout this MBA journey. My deepest thanks go to my supervisor, Dr Yvonne K Saini, for their invaluable guidance, encouragement, and constructive feedback. I am also grateful to the Faculty of Commerce, Law and Management at Wits Business School for providing a rich academic environment that fostered my growth.

To my family and friends — thank you for your unwavering support, patience, and belief in me, especially during the most demanding phases of this programme.

Lastly, I extend my appreciation to the participants who contributed to the research through their insights and time. This work would not have been possible without your generous input.

ABSTRACT

In a time where South African retail banks significantly invest in AI-driven platforms and multichannel engagement tools, the specific processes through which data-driven customisation cultivates loyalty are vague. This research integrates Artificial Intelligence (AI), the Technology Acceptance Model (TAM), Customer Relationship Management (CRM), and Commitment–Trust theory into a cohesive structural equation model to investigate the influence of personalised banking experiences on engagement, satisfaction, trust, and advocacy among four generational cohorts (Gen Z, Millennials, Gen X, Boomers).

Survey data from 190 bank customers who participated in this research indicates that, although the frequency of digital engagement and trust in data security constitute the foundation of the service environment, it is customer satisfaction – driven by genuinely meaningful, tailored interactions – that most significantly predicts Net Promoter Score (NPS) and minimises switching intentions. The direct impact of personalisation and customisation on engagement and of trust on loyalty was not substantial, indicating deficiencies in implementation and monitoring gaps in current banking analytics.

Generational analysis reveals significant disparities in AI feature uptake, highlighting the necessity for cohort-specific personalisation tactics and strategies. These findings enhance marketing theory by establishing satisfaction as the crucial mediator in the customisation-loyalty relationship and directing practitioners towards hyper-targeted offers, transparent data governance, and customised engagement approaches to convert each digital encounter into long-term advocacy.

Keywords: Data-Driven Customisation; Customer Satisfaction; Artificial Intelligence (AI); Technology Acceptance Model (TAM); Customer Relationship Management (CRM).

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LIST OF ACRONYMS

Artificial Intelligence (AI)
Average revenue per user (ARPU)
Click-Through Rate (CTR)
Commitment-Trust (CC)
Commitment–Trust Theory CC)
Customer Engagement Cycle (CEC)
Customer Lifetime Value (CLV)
Customer Relationship Management (CRM)
Customer Satisfaction Score (CSAT)
Net Promoter Score (NPS)
Search Engine Optimisation (SEO)
Technology Acceptance Model (TAM)

CHAPTER 1: INTRODUCTION

1.1. Statement of Purpose

Despite the growing spotlight on client-centric strategies such as data-driven customisation and customer engagement in retail banking, there is little research on their combined effect in emerging economies such as South Africa (Vivek et al,. 2012; McKinsey & Company, 2020). This gap underscores the necessity to investigate the inextricable links between engagement phases, including connection, interaction, satisfaction, retention, and commitment. Advocacy, engagement, and the context in which personalised data-driven services reinforce these stages (Chen et al., 2020; Monferrer, 2019).

1.2. Background of the Study

Although the focus of the study is on customisation and customer engagement, it is worth noting that retail banking in South Africa faces market share decline, increased competition, and rising regulatory costs (BusinessTech, 2016; Fin24, 2016). As a result, economic uncertainty and market dynamics have reduced client trust, threatening banks' survival (Hansen, 2014). Innovative solutions are needed to boost client engagement and competitiveness as traditional banking models fail (Komandla & Perumalla, 2014).

AI can transform banking operations, but research on its use in South African retail banking client engagement is scarce. AI has shown promise in risk management and fraud detection (Bravo, Martinez, & Pina, 2019), but this research gap must be filled to develop tailored strategies ((Murugesan & Manohar, 2019

Digital transparent, and efficient services (Ernst & Young, 2017). Artificial intelligence systems can analyse large datasets to tailor experiences, helping banks meet shifting customer expectations (Buchanan, 2019). AI improves service quality and operational efficiency, improving bank performance and customer loyalty (Pansari & Kumar, 2017a). This research will focus on morally good digital solutions to customise client engagement.

1.3. Problem Statement

Global retail banking institutions are leveraging artificial intelligence (AI), analytics, and customer relationship management (CRM) systems to provide data-driven customisation that improves engagement, satisfaction, and long-term loyalty (Murugesan & Manohar, 2019; McKinsey & Company, 2020). Although research in developed markets indicates that data-driven personalisation enhances engagement and advocacy (Bravo et al., 2019; Pansari & Kumar, 2017), the findings are fragmented, with limited evidence regarding variations in these interactions among generational segments. Current international research predominantly focuses on technology implementation rather than behavioural outcomes, neglecting the influence of customers' trust, perceived value, and satisfaction shape engagement in digital banking environments (Chen et al., 2020; Buchanan, 2019).

A significant problem facing the retail banking sector in South Africa is balancing data-driven personalisation with customer engagement. Although client involvement is increasingly acknowledged as a crucial factor in fostering loyalty and pleasure, numerous banks do not execute successful data-driven customisation strategies that meet customer expectations (Buchanan, 2019; FSCA, 2020). Even with improvements in customer engagement strategies, there is still a significant gap in the use of metrics such as Customer Lifetime Value (CLV) and Net Promoter Score (NPS) to evaluate and enhance engagement (Javornic & Mandelli, 2012; Vivek et al., 2012).

Moreover, research in emerging markets, such as South Africa, remains limited on how the relationship between data-driven customisation, generational expectations, perceived usefulness (as framed by the Technology Acceptance Model), and customer-centric practices in fostering engagement and satisfaction (Davis, 1989). Considering South Africa's rapidly transforming digital banking landscape, heightened regulatory emphasis on data protection under the Protection of Personal Information Act (POPIA), and the diverse generational demographics of banking consumers, researchers must examine the effectiveness of data-driven customisation and personalisation in improving engagement, satisfaction, and advocacy across various generations of consumers (Republic of South Africa, 2013).

Modern customers require personalised interactions; nevertheless, banks frequently encounter challenges in providing customised experiences owing to inadequate data analysis and integration (Bravo et al., 2019; Murugesan & Manohar, 2019). This disconnection not only impedes client happiness but also restricts the potential for enduring connections and brand advocacy (Pansari & Kumar, 2017; Tripathi, 2009).

Research suggests that banks must improve their understanding and utilisation of client data to optimise engagement initiatives (Chen et al., 2020; McKinsey & Company, 2020). Addressing these challenges is essential for creating strategies that align with changing consumer needs and enhancing the overall level of client engagement and personalisation in the retail banking sector.

1.4. Research Objectives

- O1: To analyse the phases of the Customer Engagement Cycle (CEC) within the South African retail banking sector, leveraging indicators such as Customer Lifetime Value (CLV) and Net Promoter Score (NPS),
- O2: To assess the impact of data-driven customisation on customer satisfaction, retention, and advocacy within the South African retail sector,
- O3: To examine how factors derived from Artificial Intelligence (AI), Technology Acceptance Model (TAM), Customer Relationship Management (CRM) and the Commitment-Trust (CC) framework interact within the Customer Engagement Cycle (CEC) to further improve engagement strategies; and
- O4: To propose a conceptual framework that integrates CLV and NPS with data-driven customisation to improve customer engagement and brand equity.

1.5. Research Questions

- Q1: What are the key stages of the Customer Engagement Cycle, and how can South African retail banks use CLV and NPS indicators or metrics to improve these phases of the cycle?
- Q2: What is the impact of data-driven customisation on customer satisfaction, retention, and advocacy in the South African retail banking sector?
- Q3: How do factors drawn from AI, TAM, CRM, and CC frameworks influence the Customer Engagement Cycle to improve customer engagement outcomes?

- Q4: What conceptual model can integrate data-driven customisation and personalisation to address engagement gaps and strengthen brand equity?

1.6. Rationale of the Study

Retail banking in South Africa risks diminishing market share, greater competition, and rising regulatory expenses (BusinessTech, 2016; Fin24, 2016). Customer trust has been eroded by economic volatility and market dynamics after the 2008 financial crisis (Hansen, 2014). Traditional banking models fail to adapt, requiring innovative solutions to boost consumer engagement and competitiveness (Komandla & Perumalla, 2014, 2014).

South African research on AI in customer engagement is limited despite its potential to alter banking operations. AI is effective in risk management and fraud detection (Bravo, Martinez, & Pina, 2019a), making local bank strategies essential (Murugesan & Manohar, 2019). Digital interactions have increased customer demand for personalised, transparent, and efficient services (Ernst & Young, 2017).

AI has proven effective in functions like risk management and fraud detection (Bravo, Martinez, & Pina, 2019a), making it vital to develop tailored strategies for local banks (Murugesan & Manohar, 2019). Customers increasingly demand personalised, transparent, and efficient services due to the rise of digital interactions (Ernst & Young, 2017).

1.7. Delimitations of the Study

Given South Africa's particular market dynamics and regulatory environment, the study will focus on retail banking only. It will focus on AI applications for customer engagement, eliminating banking applications like backend operations, compliance, and risk management unless they directly affect customisation.

The research will focus on current AI technology, customer engagement, and customisation strategies, excluding future advances. The study will also focus on a few major banks' customers, which may limit its generalisability. The study uses these factors to analyse how AI can improve client engagement and customisation in South African retail banking.

1.8. Assumptions

The underlying assumption is that banks have the appropriate technology for implementing data analytics and machine learning and that accurate consumer data is accessible for effective customisation. If privacy concerns are addressed, customers are likely to provide their data in exchange for personalised services. The regulatory environment in banking promotes data analytics by maintaining a balance between innovation and privacy. Data-driven customisation is believed to improve customer engagement, satisfaction, and loyalty, while trustworthy metrics are available to measure engagement.

Customer segments will demonstrate distinct responses to personalised strategies, necessitating customised strategies. The assumption is that banks are prepared to adopt and integrate these strategies, which will have a positive impact on consumer behaviour and increase the usage of services. In conclusion, the strategies that have been developed have been proven to be adaptable and scalable across a variety of South African retail banking institutions, thereby improving overall engagement through customisation.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

As the South African retail banking sector undergoes rapid transformation, driven by technological advancements and shifting market dynamics, understanding the interplay between these changes and customer engagement becomes increasingly crucial. This chapter aims to provide a comprehensive exploration of marketing drivers as well as influences, the current state of banking in South Africa, the impact of technological disruption, and the evolving landscape of customer engagement. By reviewing empirical literature and integrating theoretical insights, this chapter sets the stage for developing a conceptual framework that addresses these issues.

2.2. 7Ps of Marketing

Marketing is essential for fostering sustainable and successful business revenue growth through strategic identification, evaluation and pursuit of market opportunities. Kotler (2003) asserts, "…the air of marketing is to make selling superfluous," emphasising the role it plays in identifying unfulfilled customers' needs and providing customised solutions. In contrast to selling, which takes place after the production, marketing initiates the evaluation of market demands and extends throughout the product lifecycle, emphasising customer engagement, services and product enhancement and repeat business.

The 7Ps of marketing (product, price, place, promotion, people, process and physical evidence) – also referred to as the marketing mix – underpin the enhancement of customer satisfaction and loyalty in South Africa's retail banking sector (Eze et al., 2015; Reddy & Karnam, 2016a). Nonetheless, gaps persist in the integration of these concepts with digital marketing tactics to enhance customer engagement and customisation.

2.3. Consumer Behaviour

Consumer behaviour in retail banking is shaped by elements including financial literacy and privacy concerns (FSCA, 2020). Notwithstanding considerable insights, research on harnessing these factors to improve customer engagement using digital platforms remains limited (Rahman et al., 2020).

2.4. Customer Satisfaction

Customer satisfaction is evaluated frequently using the 7Ps framework (Johnson & Fornell, 1991; Tyrinopoulos & Antoniou, 2008). As essential as customer retention may be, customising customer experiences with AI and machine learning presents a significant, untapped potential for improving customer satisfaction (McKinsey & Company, 2020).

2.5. Customer Engagement

Building strong emotional connections with customers is crucial for fostering customer loyalty and setting yourself apart from business competitors (Ashley et al., 2011; Vivek, 2012). However, limited research has explored strategies to connect customer engagement with customisation tactics to maximise business growth and success (Chen et al., 2020; Monferrer, 2019).

2.6.1. Customisation

Customisation adapts products and services to the specific requirements of individual customers, aiding in brand differentiation within a saturated market. This element is essential for fostering loyalty and enhancing sales, although it necessitates greater integration with client engagement tactics (Ahn & Back, 2018; Fierro et al., 2014).

2.6.2. Customer Engagement and Customisation

The integration of customer engagement and customisation can result in increased loyalty and improved business performance. The relationship between these two concepts is inadequately explored, underscoring the necessity for strategies that foster

customised experiences that emotionally engage customers (Coelho & Henseler, 2012; Pansari & Kumar, 2017; Tripathi, 2009).

2.7. Digital Marketing

As noted by Kotler (2003), “marketing is far too important to be left only to the marketing department,” which underscores its strategic significance across various areas in an organisation, with everyone contributing towards building and maintaining relationships with clients.

Desai (2019) asserts that digital marketing has revolutionised how businesses interact with customers by utilising digital platforms to market their products, services, and brands. Digital marketing uses diverse strategic approaches, including social media, content marketing, email marketing, and search engine optimisation (SEO), which improve client interaction and facilitate data-driven customisation (Desai, 2019).

Digital marketing's capacity to leverage big data and artificial intelligence (AI) to produce highly customised consumer experiences is one of its key benefits. Deeper engagement and client loyalty are fostered by AI-driven tools that analyse consumer behaviour, forecast preferences, and deliver personalised content (Desai, 2019). Furthermore, customer relationship management (CRM) systems contribute to the enhancement of personalised interactions, the refinement of marketing strategies, and the collection and analysis of customer data within businesses (Payne & Frow, 2005).

It has limitations despite its advantages, such as expensive implementation costs, data privacy concerns and algorithmic biases (Desai, 2019). Adopting ethical AI processes, transparent data policies, and creative personalisation strategies while constantly adjusting to the changing digital landscape are all necessary for businesses to maintain customer trust and confidence.

Digital marketing has revolutionised client relationships, providing novel opportunities for customer engagement and customisation. There is a notable lack of research in this area, as evidenced by the challenges encountered by numerous banks in implementing effective changes (Kaplan & Haenlein, 2019; Patil et al., 2024).

According to Shankar (2024), artificial intelligence has the potential to significantly drive innovation in digital marketing, particularly in the areas of hyper-personalisation, predictive analytics and immersive technologies such as augmented reality.

2.8. Artificial Intelligence (AI)

Artificial intelligence significantly improves customer engagement and customisation through the implementation of personalised recommendations and predictive analytics (McKinsey & Company, 2020; Juniper Research, 2017). Artificial intelligence aids in recognising customer preferences and behaviours, making it possible for banks to customise products and services more efficiently (Soni et al., 2019). Moreover, Moreover, AI-powered solutions and tools such as chatbots offer immediate, customised support, enhancing customer satisfaction and overall engagement (Shankar, 2024).

Incorporating AI in content generation has optimised marketing strategies, enhancing productivity while ensuring high-quality and timely customer engagement (Shankar,2024).

Notwithstanding its potential, concerns such as data privacy and ethical considerations must be resolved for the optimal use of AI in customer engagement (Donepudi, 2017; Dietvorst et al., 2018). Additional research remains required on the integration of AI into customer engagement efforts, particularly on how to utilise it to strike a balance between privacy concerns and customisation.

2.9 Interconnectedness of Key Components

The complex relationship of key marketing and customer experience elements are essential for understanding data-driven customisation and customer engagement in the South African retail banking sector.

The 7Ps of Marketing affect consumer behaviour by influencing perceptions and decision-making processes (Kotler & Keller, 2016). Such behaviour directly influences the satisfaction of customers, as customised products and services that meet consumer expectations enhance experiences (Solomon, 2018).

Enhanced satisfaction cultivates engagement, strengthening advocacy, loyalty, and long-term retention (Pansari & Kumar, 2017). Engaged customers provide essential feedback and data, enabling modifications through customised offerings (Murugesan & Manohar, 2019).

Successful digital marketing strategies utilise personalisation to boost brand-consumer interactions and customer touchpoints, states Bravo et al. (2019). By evaluating large databases, improving customer insights, and maximising customised marketing efforts and initiatives, artificial intelligence (AI) plays a crucial role in this process (McKinsey & Company, 2021).

For further support of customer engagement, AI-driven tactics enable predictive analytics and hyper-personalisation, ensuring that customers have experiences that are both dynamic and relevant (Chen et al., 2020s).

The combined effect of these elements underscores a perpetual cycle wherein strategies for marketing, customer behaviour, digital innovations, and AI collaboratively enhance engagement and brand equity with the South African retail banking industry in an increasingly digital economy.

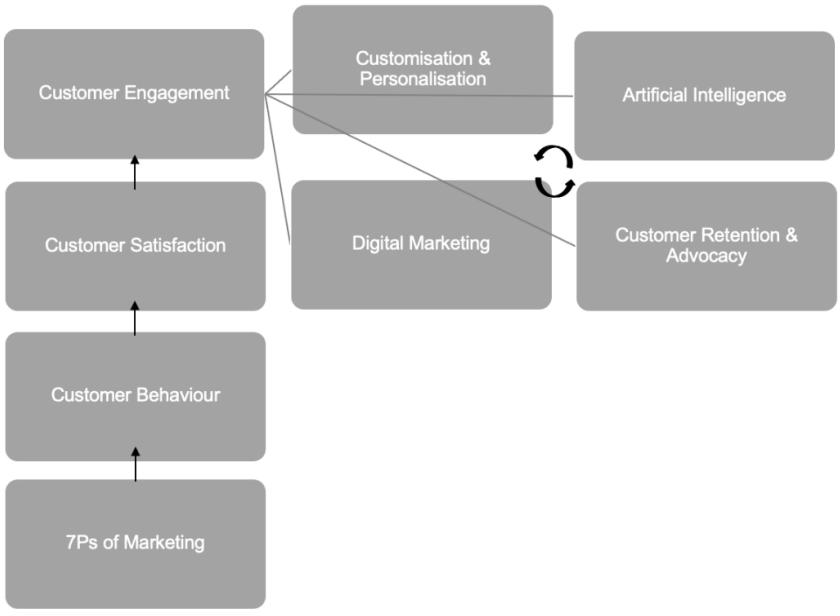


Figure 1 – Graphical representation of the interconnectedness of the key components

2.10. Analytical Framework

2.10.1 Theoretical Framework

2.10.2. Technology Acceptance Model

The integration of artificial intelligence (AI) and the technology acceptance model (TAM) in the retail banking sector of South Africa has the potential to greatly improve consumer engagement and operational efficiency. AI solutions offer tailored banking experiences and optimise operations by increasing the need for customised services (McKinsey & Company, 2021). Perceived value and ease of use are crucial components of the TAM framework for understanding technology adoption in banking (Wentzel, Diatha, & Yadavalli, 2013). Research underscores the significance of user-friendliness and perceived advantages in the acceptance of AI-powered technologies (Mhlanga & Moloi, 2023). Integrating trust into the Technology Acceptance Model (TAM), particularly with regard to data privacy and security, enhances the successful incorporation of AI in the banking sector (Al-Sharafi et al., 2016).

2.10.3. Customer Relationship Management Theory

Retail banking in South Africa is undergoing a transformation driven by the integration of AI and Customer Relationship Management (CRM) theory. AI improves customer relationship management (CRM) by automating customer interactions and analysing data to provide tailored experiences, therefore enhancing consumer engagement and loyalty (International Journal of Social Sciences and Humanities Invention, 2018; Sweeney et al., 1999). The CRM theory centres on the management of client relationships to promote customer satisfaction and loyalty, in line with the ability of AI to forecast customer needs and customise services (Pietersen & Kritzinger, 2010). According to Nene and Olawale's (2017) research, AI-driven CRM practices in the South African banking industry could increase customer satisfaction and loyalty by addressing individual preferences and concerns and resulting in data-driven marketing strategies.

2.10.4. Commitment-Trust Theory

Morgan and Hunt (1994) assert that the commitment-trust (CC) theory highlights two essential criteria for effective relationship marketing: trust and commitment. Trust

denotes the confidence clients have that their needs and desires will be prioritised, whereas commitment signifies a long-term dedication to sustaining a connection. These elements are essential for cultivating loyalty, managing uncertainty, and promoting collaborative behaviour. By integrating trust and commitment, organisations can nurture lasting relationships with customers that improve satisfaction, retention, and advocacy.

Retail banks can achieve a sustained competitive advantage by aligning customer engagement with trust and commitment, which in turn enhances customer satisfaction, loyalty, and advocacy (Pansari & Kumar, 2017).

2.10.5. Customer Engagement Cycle

In the digital age, where personalisation is paramount, retail banking relies heavily on customer engagement and customisation. Chen et al (2020) initially aimed to develop a theoretical framework for customer engagement but, later introduced a customer engagement cycle (CEC). This review analyses the relationship between these concepts using the CEC as a framework.

The term "customer engagement" describes the mental, emotional, and behavioural commitments that consumers make in a business. This includes relationships that extend beyond simple purchases, cultivating loyalty and advocacy (Sashi, 2012; Williams, 2016). Positive word-of-mouth and repeat business are two ways that engaged customers are more likely to contribute to a successful brand in the future.

Client feedback, interaction frequency, Net Promoter Score (NPS), duration, and Customer Lifetime Value (CLV) are among some of the metrics used to gauge customer engagement and brand equity (Javornic & Mandelli, 2012; Vivek et al., 2012).

Customisation is the process used to create products and services unique to each consumer's wants and needs. According to Soni et al. (2019), this strategy improves the offerings' relevance and happiness, which improves client experiences. Customisation is assessed using customer satisfaction surveys, the Personalisation Index, and usage analytics. These indicators evaluate the alignment of customisation

efforts with customer expectations and their enhancement of the entire experience (Rahman et al., 2020; Kaplan & Haenlein, 2019; BCG, 2019).

The CEC (Sashi, 2012) segments customers through stages illustrated below. Personalised marketing builds relationships (Donepudi, 2017). Continuous communication is typically boosted by AI (Juniper Research, 2017). Customised services that exceed customer expectations (FSCA, 2020) result in satisfaction. Maintaining long-term relationships requires consistent participation (Dietvorst et al., 2018). Brand loyalty: Building preference. Encouraging customer brand advocacy (Patil et al., 2024) is key. Engaging customers through continuous personalisation fosters deep customer loyalty (Kaplan & Haenlein, 2019).

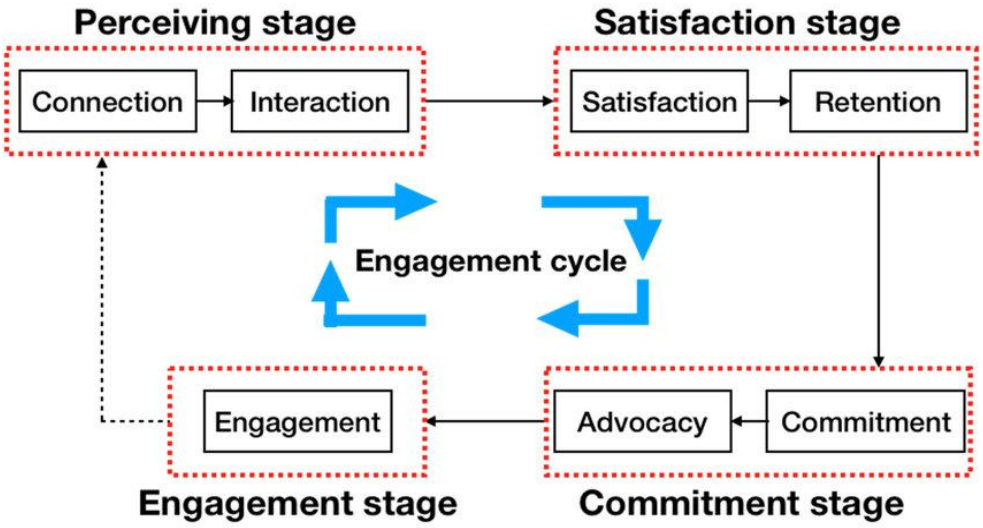


Figure 2 – Model of the customer engagement cycle

Source: Sashi (2019)

2.11. Conceptual Framework and Hypotheses Development

2.11.1. Conceptual Framework

The Customer Engagement Cycle is improved by incorporating the use of personalisation strategies, AI, and CRM, which in turn increases customer satisfaction, brand equity and retention (CE Index, 2024). The differences between generational segments influence the success rate of customisation, necessitating customised strategies (Engineering News, 2023). Subsequent research ought to investigate these

intricacies to enhance AI-driven banking methodologies while tackling ethical issues and fostering trust.

The adapted conceptual framework of the customer engagement cycle, illustrated in Figure 3, depicts how continuous growth and loyalty are ensured by the cyclical progression – from the Engagement Stage → Perceiving Stage → Satisfaction Stage → Commitment Stage, supported by theories (TAM, AI, CC, CRM) and metrics (NPS, CLV, duration, interaction frequency and client feedback). As advocates establish connections with potential new customers through recommendations and referrals, the cycle recommences following the Engagement Stage. This cyclical nature guarantees that the customer base continues to grow and strengthens its relationship with the bank.

The combined effect of data-driven customisation and client engagement constitutes the foundation of personalised banking strategies within South Africa's retail industry. The essence of data-driven customisation is in the systematic implementation of AI, CRM systems, and predictive analytics to provide customised content, products, and services to certain segmented generations of consumers (Payne & Frow, 2005; Desai, 2019; Onesi-Ozigagun et al., 2024).

While the conceptual framework below illustrates how to measure engagement, perception, satisfaction, and commitment, there remain sub-research problems to explore further how to measure data-driven customisation. It commences with customer engagement, which is assessed by their emotional connection with the brand, awareness, and satisfaction (Ladhari et al., 2019). As a result, the assumption could be that data-driven customisation tactics are activated, which utilise real-time data to provide personalised experiences that align and resonate with the target audience, customer preferences and behaviour (Hong, 2024). Dynamic updates are enabled by tools like machine learning models and CRM dashboards, which establish a continual refinement cycle (Camirelli, 2020).

The effects of this conceptual framework are noticeable in the post-customisation outcomes, which include enhanced customer loyalty, brand trust, higher purchase intention, and stronger retention rates (Udo, 2024; Ladhari et al., 2019; AgencyAnalytics, 2024). These results are crucial for maintaining sustained competitiveness in a saturated digital market. The Net Promoter Score (NPS) and

Retention Rate (RR) are critical measures that quantify the effectiveness of customisation strategies (Baquero, 2022; HawkSEM, 2024).

Therefore, Therefore, the simplified conceptual framework illustrates that data-driven customisation and strategic engagement are not merely marketing tools but rather critical enablers in accelerating the creation of intrinsic value and the promotion of customer advocacy.

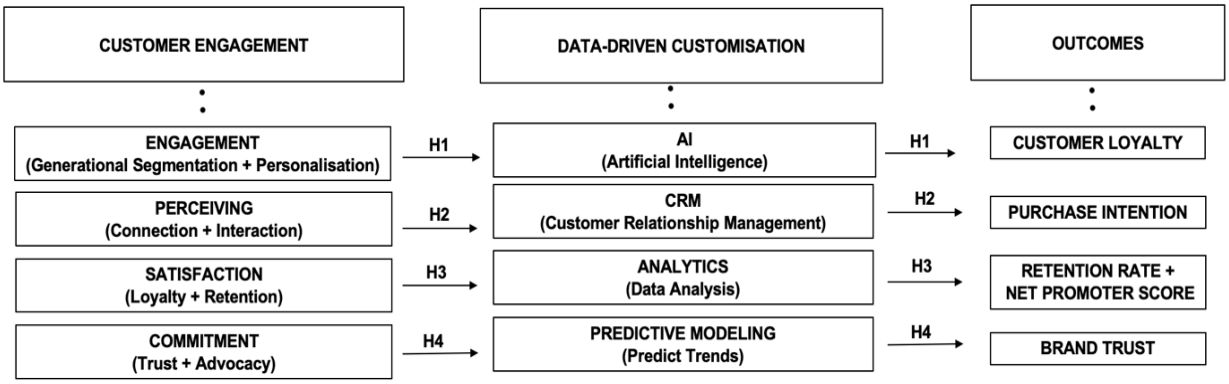


Figure 3 – Conceptual framework focusing on customer engagement and data-driven customisation

2.12. Interconnectedness of Objectives and Hypotheses Development

The conceptual framework serves as the foundation for the following hypotheses, which investigate the relationships among data-driven customisation, customer outcomes, and customer engagement in the retail banking industry in South Africa.

2.12.1. Research Hypotheses

- H1: AI-driven customisation improves key aspects of interactions with customers. The use of AI empowers banks to provide tailored, data-driven experiences that enhance client engagement, augment brand equity, and promote advocacy within various generational segments. As AI enhances accuracy in the delivery of services and responsiveness, it is anticipated to foster greater emotional and behavioural involvement among customers (Bravo et al., 2019; McKinsey & Company, 2020; Murugesan & Manohar, 2019).

- H1a: AI-driven customisation positively influences customer engagement, brand equity and customer advocacy.
- H1b: The impact of AI-driven customisation on engagement, brand equity, and advocacy differs across generational segments.
- H1c: Personalisation positively influences the adoption of technology platforms, including AI and wearable solutions, among South African retail banking customers.
- H1d: Personalisation positively influences the perceived usage and ease of use of AI-driven platforms in enhancing customer engagement.

- H2: CRM systems impact customer satisfaction and purchase intention. CRM helps banks manage client data, tailor interactions, and build long-term connections, which boosts satisfaction and drives future purchases. Retail banking requires effective CRM tactics to turn happiness into loyalty and cross-selling (Payne & Frow, 2005; Pansari & Kumar, 2017).
  - H2a: CRM systems positively influence customer satisfaction.
  - H2b: Customer satisfaction positively influences purchase intention.
  - H2c: Personalisation positively influences customers' perception of personalised banking services.
  - H2d: Personalisation significantly affects customers' trust and attitudes toward data privacy in digital banking.

- H3:Data analytics boosts consumer advocacy and retention. Analytical insights help banks discover behavioural patterns, predict consumer needs, and develop engagement strategies that reduce churn. Effective data analysis is projected to improve retention rates and Net Promoter Scores (NPS), which measure customer loyalty and advocacy (Bravo et al., 2019; McKinsey & Company, 2020).
  - H3a: Data analytics capabilities positively influence customer retention rate.
  - H3b: Data analytics capabilities positively influence NPS.
  - H3c: Customer satisfaction positively influences customer loyalty.

- H3d: Customer satisfaction positively influences brand advocacy and word-of-mouth communication.

- H4: Predictive modelling fosters brand trust and customer satisfaction. Banks can predict client preferences, customise services, and resolve concerns before dissatisfaction occurs with predictive tools. This proactive strategy builds consumer confidence, satisfaction, and long-term trust with financial institutions (FSCA, 2020; Morgan & Hunt, 1994).
  - H4a: Predictive modelling capabilities positively impact customer satisfaction.
  - H4b: Predictive modelling capabilities positively influence brand trust.
  - H4c: Customer commitment positively influences customer retention and loyalty.
  - H4d: Customer commitment positively influences brand advocacy and long-term brand trust.

2.12.2. Research Objectives

- O1: To analyse the phases of the Customer Engagement Cycle (CEC) within the South African retail banking sector, leveraging indicators such as Customer Lifetime Value (CLV) and Net Promoter Score (NPS) to determine engagement and relationship quality (Buchanan, 2019; Vivek et al., 2012).

- O2: To assess the impact of data-driven customisation on customer satisfaction, retention and advocacy within the South African retail banking sector (Bravo et al., 2019; Murugesan & Manohar, 2019).

- O3: To explore the combined effects of Artificial Intelligence (AI), Technology Acceptance Model (TAM), Customer Relationship Management (CRM) and Commitment-Trust (CC) theories inside the Customer Engagement Cycle to further improve engagement strategies and data-driven customisation (Sashi et al., 2019; Payne & Frow, 2005; Pansari & Kumar, 2017).

- O4: To propose a conceptual framework that integrates CLV and NPS with data-driven customisation to improve customer engagement and brand equity (McKinsey & Company, 2020).

The above objectives are cohesively aligned with the sequential progression of the conceptual framework, where customer engagement serves as the basis for data-driven customisation, and both technological and relational drivers (AI, CRM, analytics, and predictive modelling) propel measurable customer outcomes. Objective 1 centres on the Customer Engagement Cycle (CEC) and its metrics (CLV and NPS), whereas Objectives 2 and 3 expand this analysis by the interplay of AI, TAM, CRM, and Commitment–Trust theories in improving satisfaction, retention, and advocacy. Objective 4 consolidates these links into a conceptual framework that integrates data-driven customisation with engagement results, including brand equity and trust. This alignment provides theoretical coherence and empirical consistency between the study's objectives, hypotheses, and conceptual framework.

Figure 4 on the next page explores the cyclical progression of South African retail banking clients from initial connection to brand advocacy. Every stage and phase adds to a feedback loop that raises value and engagement (Bravo et al., 2019; McKinsey & Company, 2020).

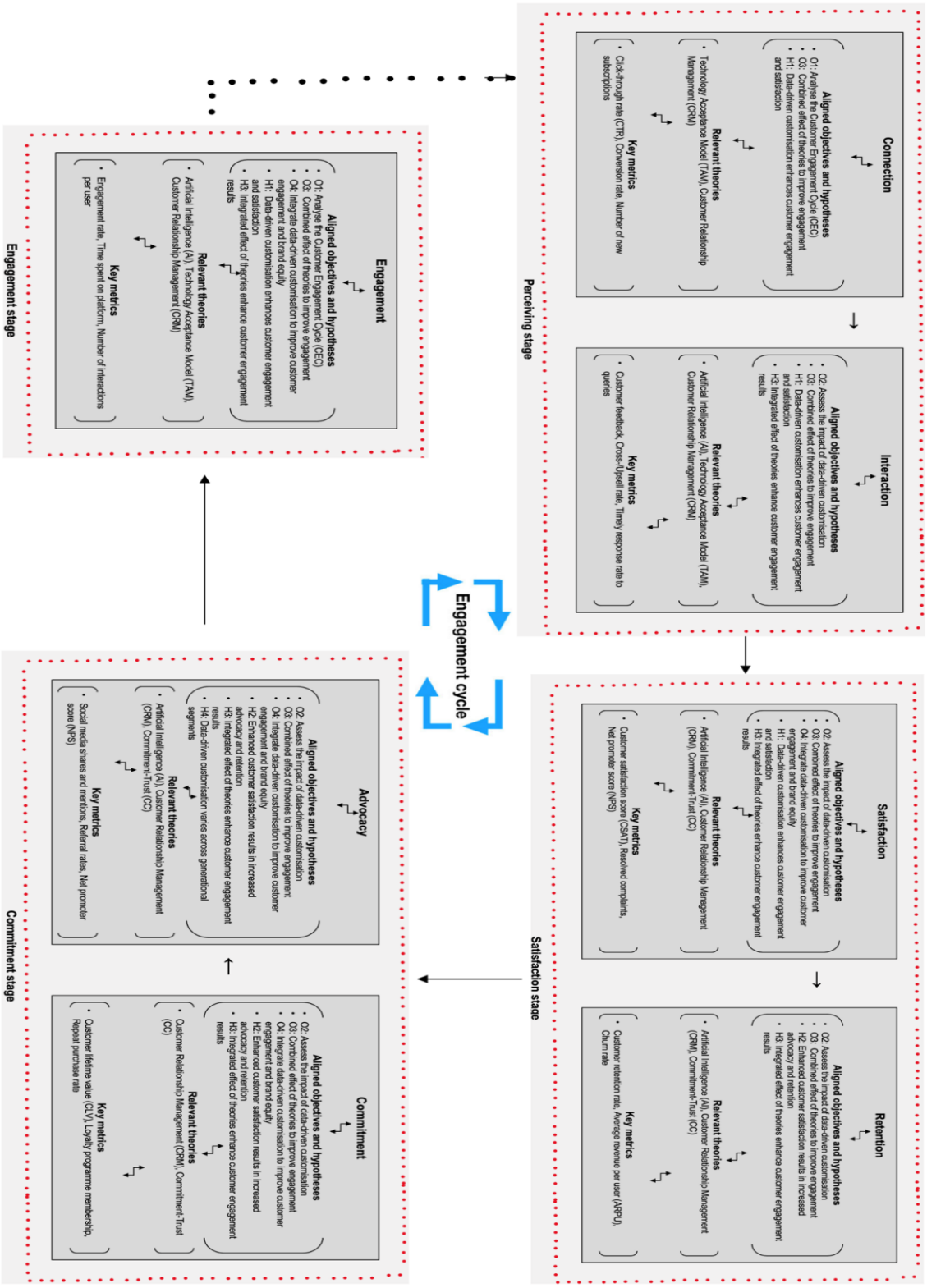


Figure 4 – Adapted model of the customer engagement cycle integrating objectives and hypotheses further

Source: Sashi (2019)

Below is a brief explanation of the interconnectedness of Figure 4's adapted model of the customer engagement cycle in a retail banking context.

- Connection: The initial touchpoint with customers, shaped by TAM and CRM, guarantees smooth integration of banking services. Metrics such as CTR and new signups evaluate success (Sashi et al., 2019; Payne & Frow, 2005).
- Interaction: AI, TAM and CRM provide active interactions between customers and the bank to customise experiences. Metrics such as feedback scores monitor service quality, which increases satisfaction according to H3 (McKinsey & Company, 2020).
- Satisfaction: Building trust and fostering loyalty are the results of meeting expectations, which are driven by AI and CC. Metrics such as CSAT and NPS assess satisfaction levels, consistent with H2 (Bravo et al., 2019).
- Retention: CC and CRM cultivate enduring relationships, utilising indicators such as retention rates and ARPU to assess long-term involvement (Pansari & Kumar, 2017; Payne & Frow, 2005).
- Commitment: The relationship is actively invested in by customers as loyalty evolves into commitment. Metrics such as CLV indicate their worth, directed by CC and consistent with Hypothesis 3 (H3) (Sashi et al., 2019).
- Advocacy: Loyal consumers generate new connections by promoting the brand through referrals. AI and CRM enhance advocacy initiatives, utilising measures such as NPS and referral rates to assess effectiveness (Bravo et al., 2019; Payne & Frow, 2005).
- Advocacy: Loyal consumers generate new connections by promoting the brand through referrals. AI and CRM enhance advocacy initiatives, utilising measures such as NPS and referral rates to assess effectiveness (Bravo et al., 2019; Payne & Frow, 2005).
- Engagement: This phase promotes significant client engagement through AI-driven interactions. Engagement rates serve as indicators of participation levels, correlating with H1 and O1 (Murugesan & Manohar, 2019).

2.12.3. Research Sub-Problems

Even though data-driven marketing has advanced significantly, there are still few quantitative insights available on how different generations react to data-driven customisation in South African retail banking (Desai, 2019; Onesi-Ozigagun et al., 2024). This study aims to further examine four interconnected sub-problems:

- Engagement and Retention Metrics: Although key performance metrics like CTR and NPS, are employed in various types of marketing evaluations (HawkSEM, 2024; AgencyAnalytics, 2024; Fahlevi et al., 2022), limited insights are explored about how specifically applicable and relevant they are to various demographics and generational segments to the context of South African retail banking.
- Perceptual distinction among generational segments: An understanding of how different age segments (e.g., Baby Boomers, Gen X, Millennials, Gen Z) perceive and react to personalisation strategies in retail banking contexts is limited (Desai, 2019; Onesi-Ozigagun et al., 2024).
- Loyalty driven by predictive analytics: The utilisation of predictive analytics to enhance satisfaction and foster long-term loyalty via proactive and tailored interactions with customers is increasingly prevalent globally; however, its impact on generations within the South African retail banking industry necessitates empirical validation (Baek et al., 2023; Onesi-Ozigagun et al., 2024, Wang & Kim, 2020).
- Relationship between relevancy, privacy and trust: The efficacy of data-driven customisation is significantly interdependent on perceived informativeness, relevance and brand trust; and alignment with data privacy, especially when targeting tech-savvy yet privacy-conscious consumers (Faradhilla, n.d.; Kannan & Li, 2017; MediaCulture, 2024).

All of these elements are essential for making certain that customisation initiatives promote, rather than obstruct, long-term and sustained engagement.

2.13. Conclusion

Customisation and engagement strategies are interconnected, as evidenced by the direct alignment of the CEC's phases and metrics with research objectives and hypotheses (Sashi et al., 2019). By investigating these relationships, this research will enhance an understanding of the manner in which data-driven personalised banking solutions influence engagement, satisfaction, and brand equity in the South African retail banking sector (Vivek et al., 2012; McKinsey & Company, 2020).

South African retail banks can improve customer engagement by incorporating the AI, TAM, CC, and CRM theories. This approach creates personalised experiences that build loyalty and satisfy customers (FSCA, 2020; BCG, 2019; McKinsey & Company, 2020). The Customer Engagement Cycle organises relationship-building, while AI improves personalisation and reactivity (Sashi et al., 2019; Juniper Research, 2017). Additionally, TAM helps banks analyse technological adoption hurdles and CRM systems gather customer data. These frameworks are essential for digital competitiveness as customer expectations change (Payne & Frow, 2005; Rahman et al., 2020; Eze et al., 2015; ResearchGate, 2013).

CHAPTER 3: RESEARCH METHODOLOGY

3.1. Introduction

The research being investigated looked into data-driven customisation and customer engagement in South Africa's retail banking industry. It focused on the variables that determine customer engagement, the effects of customisation on customer satisfaction and loyalty, and the impact of technology improvements. The goal of the study was to offer insights into how data-driven tactics are being used to optimise consumer experiences.

3.2. Research Design

A quantitative research methodology was used to gather comprehensive data, incorporating a structured survey alongside secondary data from credible industry reports, white papers, and case studies. This methodology is consistent with the positivist worldview, which posits that reality can be objectively quantified through empirical observation and statistical analysis. The integration of primary and secondary data improved the study's validity and contextual richness by facilitating a comparison between observed survey findings and recognised industry standards. Reliability and validity were confirmed using internal consistency testing with Cronbach’s alpha and Composite Reliability (CR), while construct validity and discriminant validity were evaluated through factor loadings and the HTMT criterion. This design established a robust framework for examining the correlations among customer engagement, data-driven customisation, satisfaction, and advocacy in the South African retail banking sector (Creswell & Creswell, 2018; Hair, Hult, Ringle, & Sarstedt, 2021; Saunders, Lewis, & Thornhill, 2019).

3.3. Data Collection Methods

A structured survey and secondary data analysis were used to gather data. While quantitative insights garnered from industry reports, white papers, and case studies will offer insights into data-driven consumer perception and customisation initiatives, surveys will collect quantitative data on customer engagement and satisfaction (Dawes, 2020).

3.3.1. Population

The population comprised retail banking customers in South Africa across various demographics such as geographic location (provinces), generational segmentation, gender, highest level of education, employment status, monthly household income and their primary bank. This diverse group ensures a holistic view of both customer perspectives and internal bank strategies (Guzovski et al, 2022).

3.3.2. Sample and Sampling Method

To guarantee representation from a variety of banking institutions and demographic groups, a stratified random sampling approach was applied. The study aimed to attain statistical significance and depth with a sample size of approximately 150 clients and received responses from 190 respondents (Hair et al., 2010).

3.4. Research Instrument

A structured questionnaire for retail banking customers formed part of the research instrument. Customer engagement components, loyalty, satisfaction, and awareness, as well as their experiences of technology innovations, were covered in the questionnaire. The questionnaire was separated into five sections:

- Section A: Demographics and Generational Segment-Specific
- Section B: Engagement and Data-Driven Customisation – Technology Platforms, AI, and Wearable Tools
- Section C: Perception and Data-Driven Customisation – Personalised Banking Services and Privacy Section
- Section D: Satisfaction and Data-Driven Customisation – Loyalty and Brand Advocacy
- Section E: Commitment and Data-Driven Customisation – Retention, Loyalty, and Brand Advocacy

The industry white papers and reports (Kumar et al., 2019) focused on the challenges involved in implementing data-driven customisation and customer engagement.

3.5. Data Analysis Strategies and Interpretation

To identify trends and correlations, quantitative survey data was analysed using descriptive and inferential statistics. Thematic analysis of quantitative industry data was employed to identify significant themes and insights. Qualtrics XM, JASP, and the SEMinR package were used for data analysis because of their broad capacity for processing both quantitative and qualitative data, their sophisticated analytical tools that allow for in-depth review and interpretation of complex datasets, and their user-friendly interfaces (Qualtrics, 2021). The reliability and validity of the study findings will be strengthened by data triangulation (Miles, Huberman, & Saldana, 2014).

3.6. Limitations

Possible constraints included response bias, the study's narrow emphasis on South Africa, limiting its generalisability, and the difficulties in combining quantitative data from industry reports and respondents' survey responses. Rigorous methodologies for sampling and triangulation are examples of mitigation approaches (Creswell & Plano Clark, 2018).

3.7. Quality Assurance

Pilot testing of the research tools and standardisation of data collection techniques were carried out to guarantee quality. To preserve data integrity, there were frequent audits and reviews by my supervisor (Hair et al., 2010).

During the data analysis phase, the hypotheses were refined to better correspond with the operational constructs evaluated in the structural model. The initial hypotheses were conceptually expansive to embody theoretical integration (AI, TAM, CRM, and Commitment–Trust frameworks), whereas the amended hypotheses closely align with the specific pathways examined in the model (e.g., Personalisation → AI, Satisfaction → Loyalty). This refinement ensured conceptual coherence and empirical validity between the literature review and the findings of model testing (McKinsey & Company, 2020; Pansari & Kumar, 2017).

3.8.1 External Validity (or Transferability)

While the technique and insights can be applied to different settings, increasing transferability, the results of the research were contextually limited to the South African retail banking industry (Lincoln & Guba, 1985).

3.8.2. Internal Validity (or Credibility)

Data triangulation through record-keeping of the study procedure, procedure and preservation of participant anonymity was used to guarantee credibility. Maintaining anonymity promoted truthful answers and lessened the possibility of biases, confirming the results in the context of the study (Merriam & Tisdell, 2015).

3.8.3. Reliability (or Dependability)

The utilisation of proven research instruments such as Qualtrics XM and SEMinR packaged, thorough documentation and uniform data collection practices contributed to reliability. This guarantees the long-term reliability of the study (Guba & Lincoln, 1994).

By implementing these strategies, the study aims to uphold high standards of validity and reliability, ensuring that the research findings are both accurate and relevant.

4.6.1. Ethical Considerations

Information sharing, voluntary engagement, and informed consent are examples of ethical issues. Approval from the university's research ethics committee was obtained prior to data collection commencing. Survey respondents were guaranteed anonymity to preserve their right to privacy and promote open communication (Resnik, 2020).

Moral concerns in research emphasise adhering to principles of secure, honest, and honourable conduct to avoid ethical lapses (Gerrard, 2021). In compliance with the Protection of Personal Information Act (POPIA) 4 of 2013, all data was collected, processed, and stored only for academic research purposes. To ensure ethical data collection and evaluation, the following practices were implemented:

1. Participants were fully informed about the study's purpose, their rights, and data use, and provided written consent, with the option to withdraw at any time.
2. Responses were kept private, anonymised, and securely stored to protect participants' identities.
3. Data will be secured using protected online platforms and anonymised to further ensure participant privacy. Storage and disposal will be for a period of five years maximum after the completion of the study, in line with university policy, and will then be permanently deleted to protect participant privacy and uphold POPIA requirements (Republic of South Africa, 20213).
4. The study avoided intrusive questions, provided necessary support, and ensured participants were not made uncomfortable or placed in a position of risk.
5. The research respected the cultural conventions and sensitivities of participants to maintain integrity and inclusivity.
6. The study provided clear details about its goals and methods, and reported results truthfully without exaggeration to uphold the principles of academic honesty and integrity (Gerread, 2021).

CHAPTER 4: RESEARCH RESULTS AND DISCUSSION

4.1. Introduction

This chapter provides the quantitative results of the online survey that was given to a stratified sample of retail banking customers in South Africa using Qualtrics. It outlines the results of the study through both descriptive and inferential statistics. The survey received 190 respondents. The questionnaire was structured into five sections, each intended to align with the study's theoretical premises, objectives and hypotheses.

The sections were measured on validated measurements or scores, such as the 5-point Likert or 0 – 10 NPS scales. The survey was pilot-tested for clarity and reliability before full distribution. Qualtrics' secure platform guaranteed the respondents' anonymity, optimised data collection, and enabled export for subsequent statistical analysis (Qualtrics, 2021). The following sections will present descriptive and inferential statistics, reliability and validity analysis, and hypothesis testing in line with the research objectives.

4.2 Descriptive and Inferential Statistics

Descriptive statistics offer a concise summary of the demographics of our respondents and the primary study variables. We include means, standard deviations, and frequency distributions for digital engagement (Desai, 2019), perceptions of personalised services and privacy (Faradhilla et al., 2022), satisfaction (Pansari & Kumar, 2017), and commitment outcomes such as loyalty and retention (AgencyAnalytics, 2023). While inferential statistics ascertains if observable differences or correlations in data or hypothesis testing are statistically significant, implying they are implausible to have emerged by chance. These preliminary insights establish the foundation for reliability assessments and hypothesis evaluation.

4.2.1 Section A: Demographics and Generational Segment-Specific

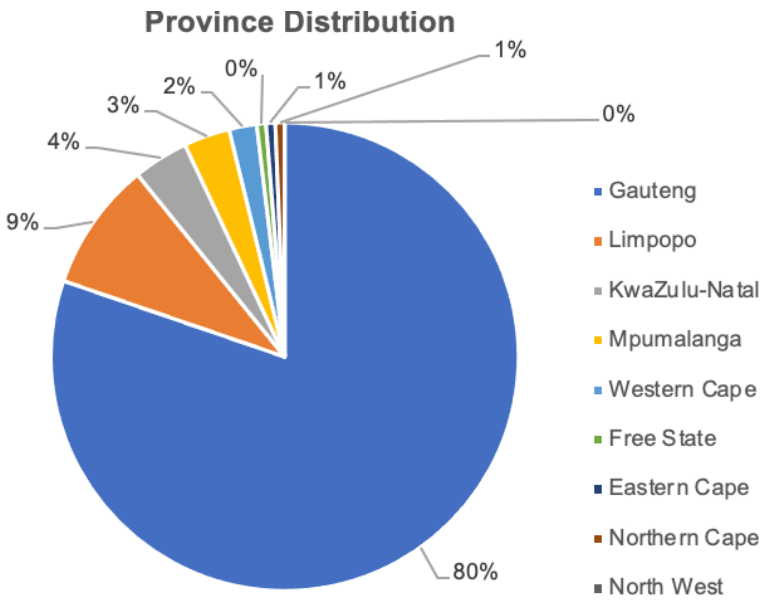


Figure 5 – Demographic distribution by province

The data in Figure 5 indicates that 80% of respondents are based in Gauteng, followed by Limpopo (9 %), KwaZulu-Natal (4%), Mpumalanga (3%), Northern Cape (2%), and just 1% each in the Eastern and Western Capes. No responses were recorded from the Free State and Northern Cape provinces. The sample is heavily skewed toward Gauteng, which may limit generalisability to other provinces.

This geographic profile indicates a significant urban concentration in Gauteng, South Africa's economic centre, whereas smaller provinces and rural regions are inadequately represented. Consequently, insights regarding digital banking engagement, adoption of AI, and data-driven customisation may predominantly represent the experiences and infrastructure of urban consumers in Gauteng. Future iterations of the survey should incorporate targeted outreach or weighting modifications to achieve a more equitable province representation (Onesi-Ozigagun et al., 2024; Stats SA, 2024).

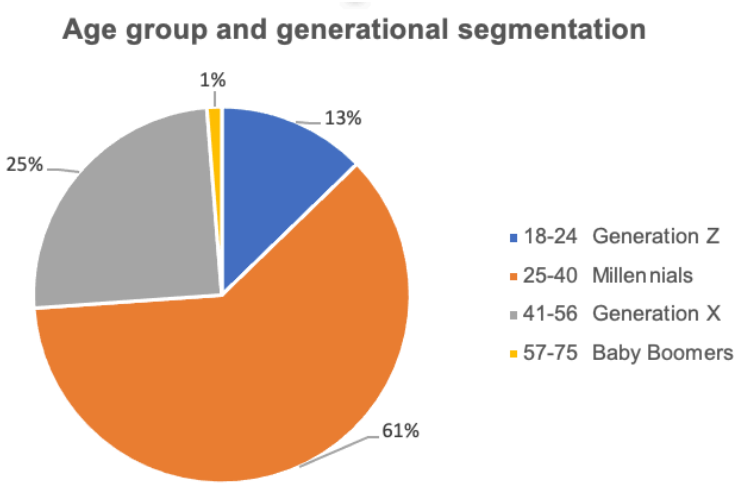


Figure 6 – Age group and generational segmentation

As observed in Figure 6, 61% of respondents are Millennials (ages 25 – 40), 25% are Generation X (ages 41 – 56), 13% are Generation Z (ages 18 – 24), and only 1% are Baby Boomers (ages 57–75). This indicates that Millennials dominate the sample, aligning with their tech-savvy nature and higher adoption of digital banking.

This significant emphasis on Millennials aligns with overarching trends indicating that this demographic is the most engaged in digital banking adoption (Engineering News, 2023). The smaller representation of Generation Z indicates an emerging, although increasing, engagement among younger users, whereas the very low response rate from Baby Boomers signifies a sluggish adoption of modern digital and wearable banking technologies within older demographics (Salinas, 2021). Therefore, conclusions about data-driven customisation and digital engagement must be understood considering this generational bias, and future data collections may require focused outreach to generational segments that are underrepresented to get a more even age distribution.

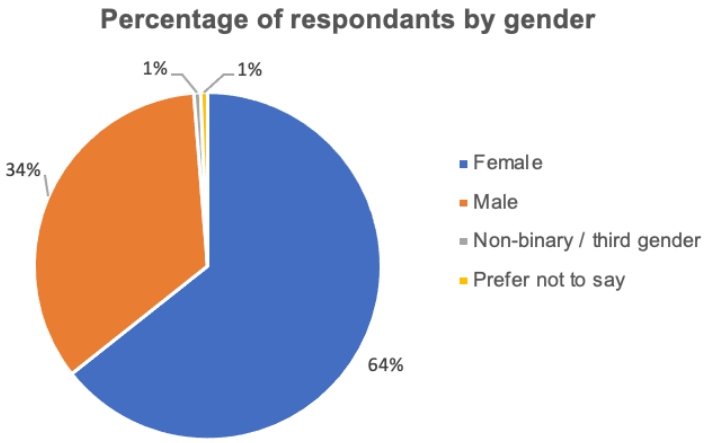


Figure 7 – Percentage of respondents by gender

Females are overrepresented at 64%, which may introduce bias in gender-based analysis. While 34% identify as male, 1% non-binary or third gender, and the other 1% prefer not to say.

This female-skewed sample diverges from the overall banking demographics, which typically exhibit a more balanced gender distribution (Engineering News, 2023). This finding also reflects that women frequently participate in research surveys and engage more with digital financial tools (Salinas, 2021). When analysing engagement and customisation outcomes, it is essential to account for this gender disparity, as preferences for AI-driven personalisation and satisfaction metrics may differ by gender.

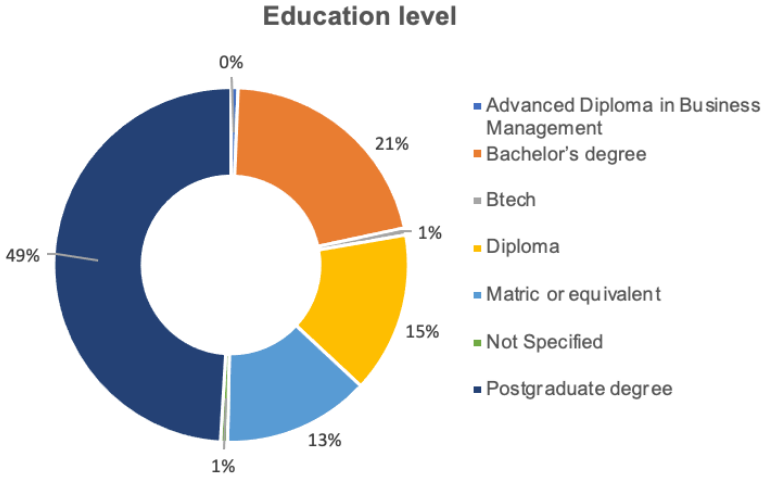


Figure 8 – Education level

Most respondents hold advanced diplomas in business management at 49%, which may influence their expectations for personalised banking features. 21% hold a bachelor's degree, 15% reported a diploma, and 13% indicated a matric (or equivalent) as their highest qualification. Only 1% respectively fell into the BTech and Not Specified categories, and no respondents indicated a postgraduate degree.

The sample is skewed towards banking customers who are formally qualified, indicating they are likely more digitally proficient and open to data-driven personalisation (Desai, 2019). Given that a majority own post-matric qualifications or higher, these respondents are inclined to utilise more sophisticated digital and AI functionalities (Engineering News, 2023). The minimal presence of postgraduate and BTech holders suggests a possible gap in perspectives from both the most and least formally credentialed groups, which may affect perceptions of advanced customisation solutions.

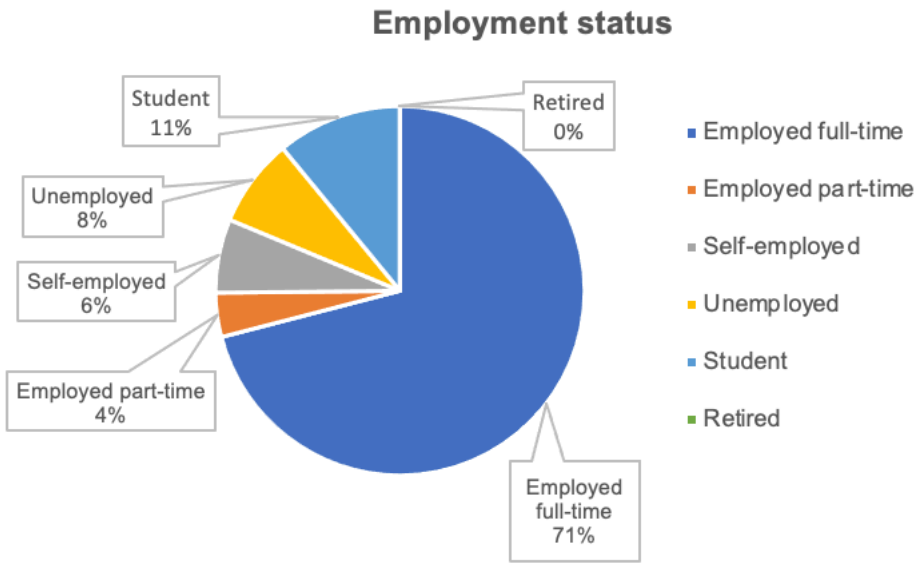


Figure 9 – Employment status

The vast majority of respondents, at 71%, have full-time employment, which may skew perceptions of banking needs (for example, stability vs. flexibility). While the smaller percentages are students (11%), unemployed (8%), self-employed (6%), part-time (4%), and retired (0%).

The significant proportion of respondents with full-time employment indicates that the sample predominantly consists of individuals with stable income sources, who are likely to have greater accessibility to and demand for advanced digital banking functionalities (Onesi-Ozigagun et al., 2024). Students and unemployed respondents have little representation compared to the working population. Their banking requirements and digital engagement behaviours may vary considerably, thus skewing overall results towards the behaviours of employed professionals. While self-employed respondents may prioritise customising differently, emphasising cash-flow tools and real-time data (Desai, 2019).

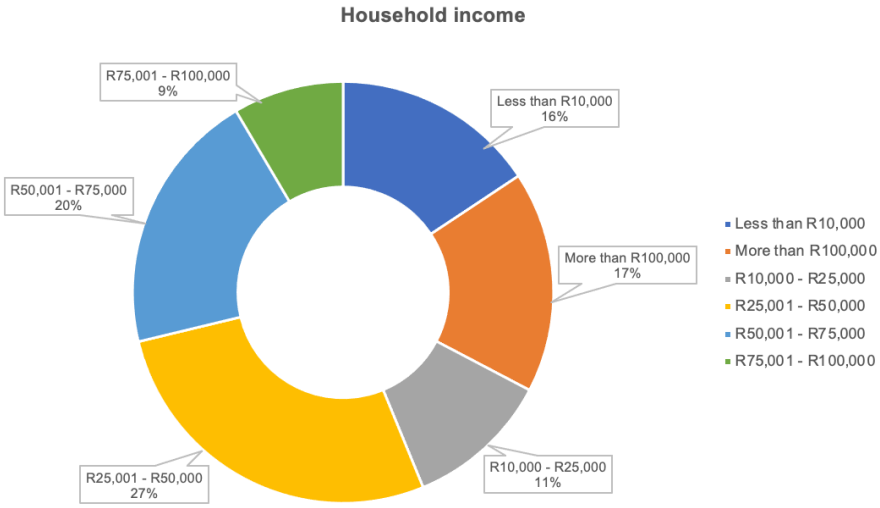


Figure 10 – Monthly household income by range

Figure 10 above suggests that the respondents are predominantly middle-income earners. 27% of respondents say their household makes between R25,000 – R50,000 per month. 20% are in the R50,000 – R75,000 range. 17% earn more than R100,000, 16% earn less than R10,000 monthly. 11% make between R10,000 – R25,000 while 9% fall between R75,000 - R100,000 and 2% did not disclose their income.

The above breakdown indicates that the majority of participants are in the upper-middle segment of South Africa's income spectrum, implying they likely possess both the resources and inclination to utilise modern digital and AI-driven banking capabilities (Stats SA, 2024). Respondents with lower incomes (≤R25,000) constitute about 26% of the sample, implying their viewpoints are still represented, although marginalised compared to those of higher earners. In analysing data-driven

customisation and digital engagement outcomes, it is crucial to understand how income level, associated with technological access and purchasing power, may influence customer preferences and behaviours (Onesi-Ozigagun et al., 2024).

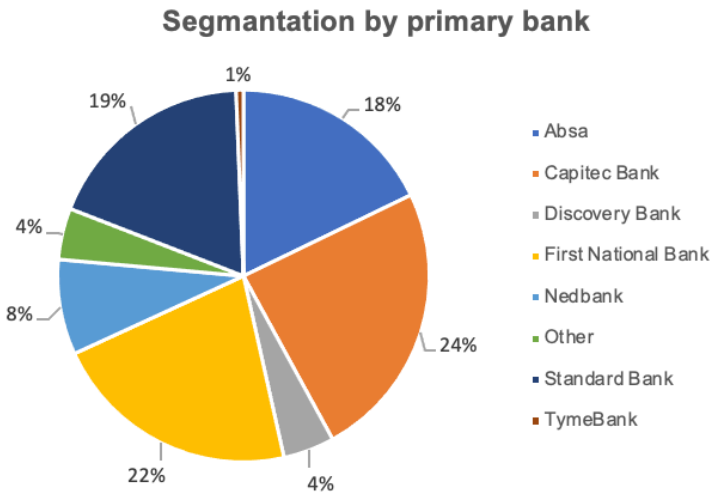


Figure 11 – Segmentation by primary bank

The segmentation by primary banking institution reveals that respondents are grouped among the "big four" retail banks of South Africa: Capitec Bank (24%), First National Bank (22%), Standard Bank (19%), and Absa (18%). TymeBank accounts for just 1% of the sample; a smaller number of respondents bank with Nedbank (8%), Discovery Bank (4%), or other institutions such as Investec at 4%.

The significant presence of Capitec, FNB, Standard, and Absa clients suggests that the sample predominantly represents consumers of well-established, mainstream banking systems characterised by comprehensive digital services and data-driven solutions (FSCA, 2020). The lower presence of challenger and digital-only banks (such as Discovery, TymeBank) indicates that insights into more innovative or emergent methods of data-driven customisation may be undervalued. When generalising data about engagement with AI features and tailored services, it is crucial to acknowledge this concentration among traditional retail bank clientele. Future studies may oversample digital challengers to encompass the complete range of South African retail banking experiences.

4.2.2. Section B: Engagement and Data-Driven Customisation – Technology Platforms, AI and Wearable Tools

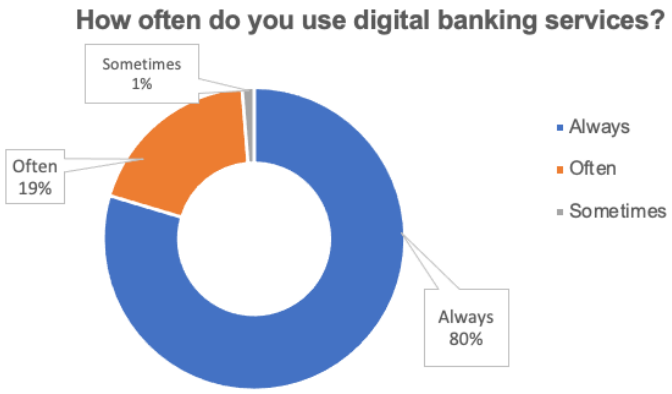


Figure 12 – Digital banking services frequency

According to the above frequency data, just 1% of respondents use digital banking services sometimes, 19% use them often, and 80% always use them, with 0% recorded as never or rarely, respectively. This practically universal acceptance of digital channels in daily banking by South African consumers reflects their acceptance of these channels (Engineering News, 2023.

From the standpoint of the Technology Acceptance Model, the elevated frequency of "always" usage indicates that respondents regard digital banking services as both beneficial and user-friendly (Davis, 1989). These results affirm that digital engagement is essential for subsequent data-driven customisation efforts in the retail banking industry (Onesi-Ozigagun et al., 2024).

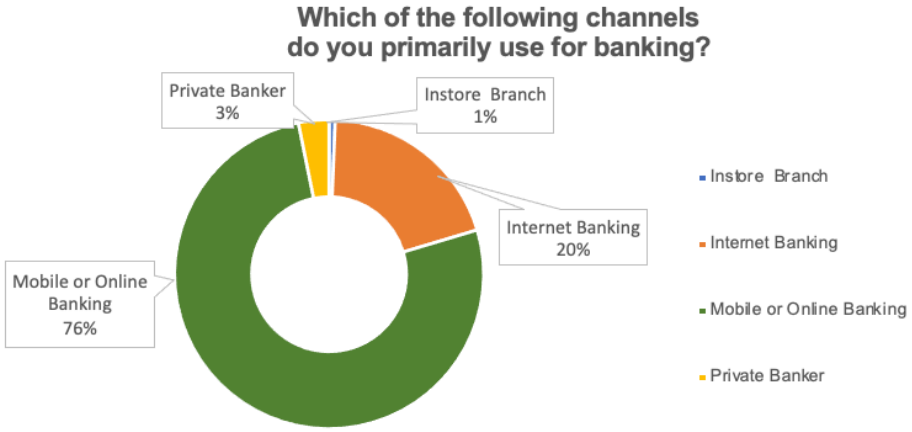


Figure 13– Channels used for banking

Based on the data in Figure 4.9, 76 % of respondents primarily use mobile or online banking, while 20% rely on internet banking. 3% deal through a private banker, and 1% usually visit an in-branch site. There were no respondents (0%) who recorded using retail store banking services through money transfers.

This spread highlights that South African retail banking consumers predominantly favour mobile channels for access, reflecting global trends in digital banking adoption (Engineering News, 2023). From the vantage point of the Technology Acceptance Model, the widespread adoption of mobile and online banking indicates a high perceived usefulness and ease of use for these platforms (Davis, 1989). The limited dependence on branches and private bankers underscores the essential need to enhance mobile and web interfaces for data-driven customisation initiatives in this market (Onesi-Ozigagun et al., 2024).

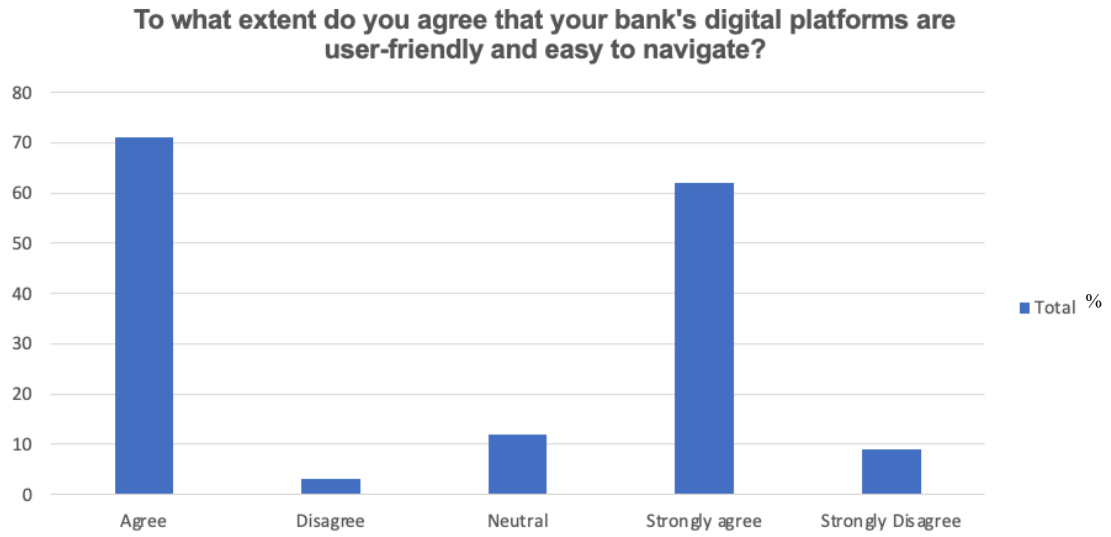


Figure 14 – Digital platform usability and navigation

The data shows positive sentiment with 62% of respondents strongly agree and 70% of them agreeing that their bank's digital platforms are easy to navigate and are user-friendly. While 12% neutral, 3% disagree, and 8% strongly disagree.

The findings demonstrate an overall favourable sentiment regarding the usability of digital banking platforms among South African retail banking clients. The elevated ease-of-use scores corroborate the Technology Acceptance Model's assertion that

perceived ease of use influences user adoption (Davis, 1989). Furthermore, this user-friendliness likely constitutes an essential basis for effective data-driven customisation efforts, since platforms must first be navigable before customised features can provide value (Desai, 2019).

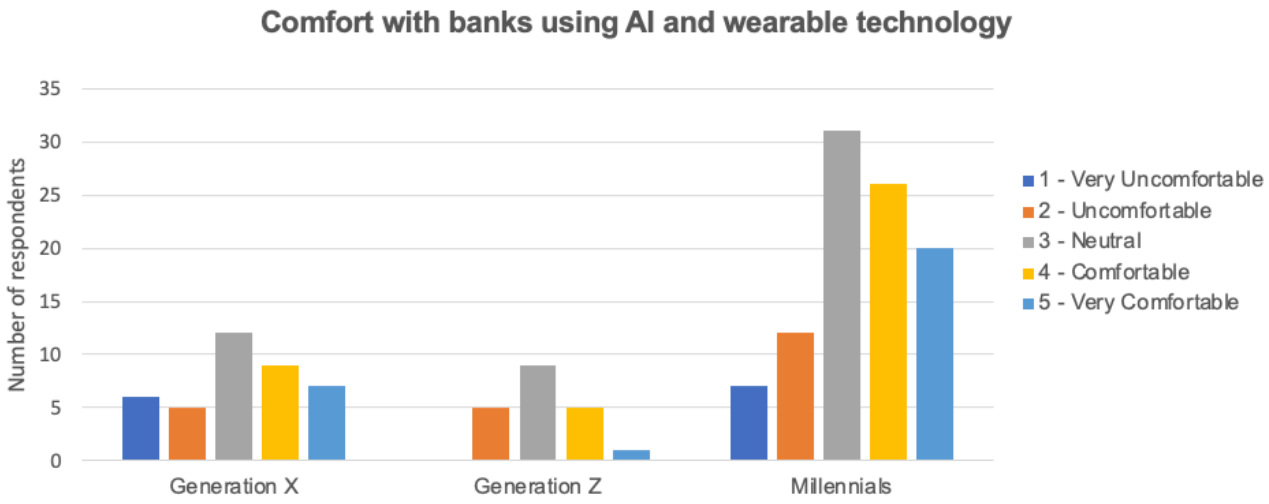


Figure 15 – Comfort with banks using AI and wearable technology

Comfort with AI-enabled and wearable banking tools differs notably by generation. Among Millennials, 48% feel comfortable or very comfortable, 32% are neutral, and 20% report discomfort. Generation X respondents show 41.0 % comfort, 30.8 % neutrality, and 28.2% discomfort. Generation Z are less at ease, with 30% comfortable, 45% neutral, and 25% feeling uncomfortable.

This disparity reveals markedly reduced adoption of AI-driven solutions among the oldest demographic, emphasising the necessity for banks to streamline and enhance the promotion of these technologies to foster engagement with Baby Boomers. These patterns reflect insights from the Technology Acceptance Model, indicating that perceptions of ease of use differ based on past digital exposure (Davis, 1989).

Baby Boomers: How often do you interact with digital features such as chatbots, biometric recognition, or AI-driven assistants provided by your bank?

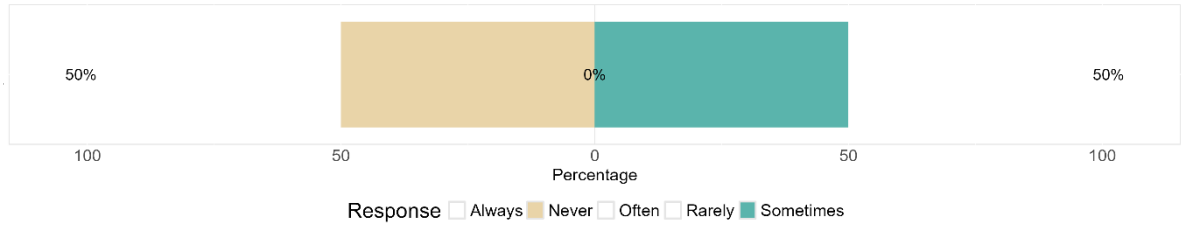


Figure 16.1 – Frequency of interaction with bank digital features among Baby Boomers

Interaction with advanced digital features is minimal for the Baby Boomer generation: 50% of them never use chatbots, biometric log-ins, or AI assistants, while the other 50% interact with these features sometimes. None of the Baby Boomers indicated using them often or always.

Generation X: How often do you interact with digital features such as chatbots, biometric recognition, or AI-driven assistants provided by your bank?

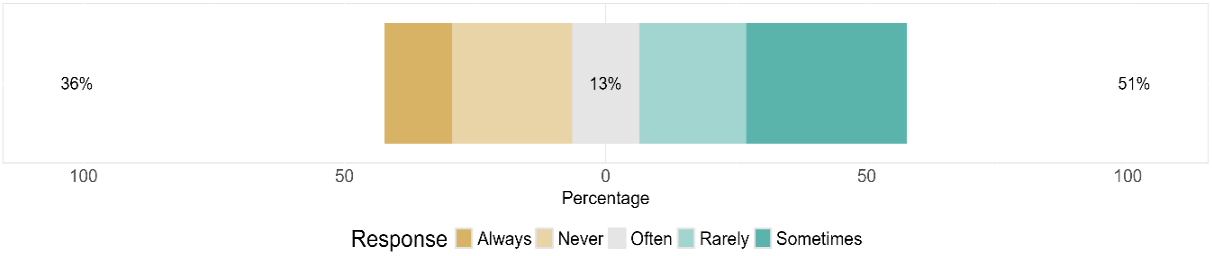


Figure 16.2 – Frequency of interaction with bank digital features among Generation X

Of the 39 Generation X respondents, 51% sometimes interact with biometrics, chatbots, or artificial intelligence assistants; 36% never use these features, and 13% rarely use them.

None of the respondents mentioned often or always interacting as a response. This indicates that although more than half of Gen-Xers have experimented with these digital tools, a significant portion remains disengaged, underscoring an opportunity for retail banks to enhance education, communicate better value, and streamline these technologies to promote wider use among this cohort.

Generation Z: How often do you interact with digital features such as chatbots, biometric recognition, or AI-driven assistants provided by your bank?

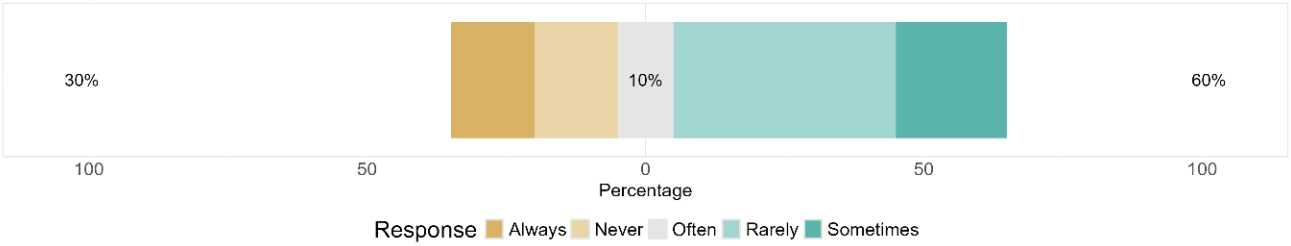


Figure 16.3 – Frequency of interaction with bank digital features among Generation Z

There were 20 Generation Z respondents; 30% said they always interacted with chatbots, biometrics, or AI assistants; 20% said they never used these features; 10% said they used them often; 20% said they used them rarely, and 20% said they used them sometimes. This mixed adoption – with 40% using them often or always – highlights that even digital natives have differing engagement with advanced banking capabilities and tools, suggesting banks must simplify and better promote these features to capture Gen Z's interest.

Millennials: How often do you interact with digital features such as chatbots, biometric recognition, or AI-driven assistants provided by your bank?

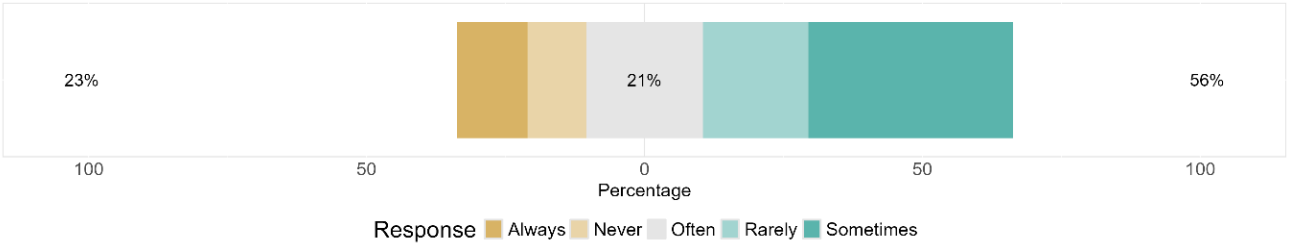


Figure 16.4 – Frequency of interaction with bank digital features among Millennials

23% of Millennials always engage with chatbots, biometric log-ins, or artificial intelligence assistants; 28% sometimes, 21% use them often, 20% rarely, and 8% never do. Therefore, even if almost one in four Millennials are regular users, most share (49%) engage only sporadically (often or sometimes), suggesting a chance for banks to increase habitual use by raising the visibility and relevance of these digital tools.

The patterns across Figures 15.1 to 15.4 reflect insights from the Technology Acceptance Model, indicating that perceptions of ease of use differ based on past digital exposure (Davis, 1989).

4.2.3 Section C: Perception and Data-Driven Customisation – Personalised Banking Services and Privacy Section

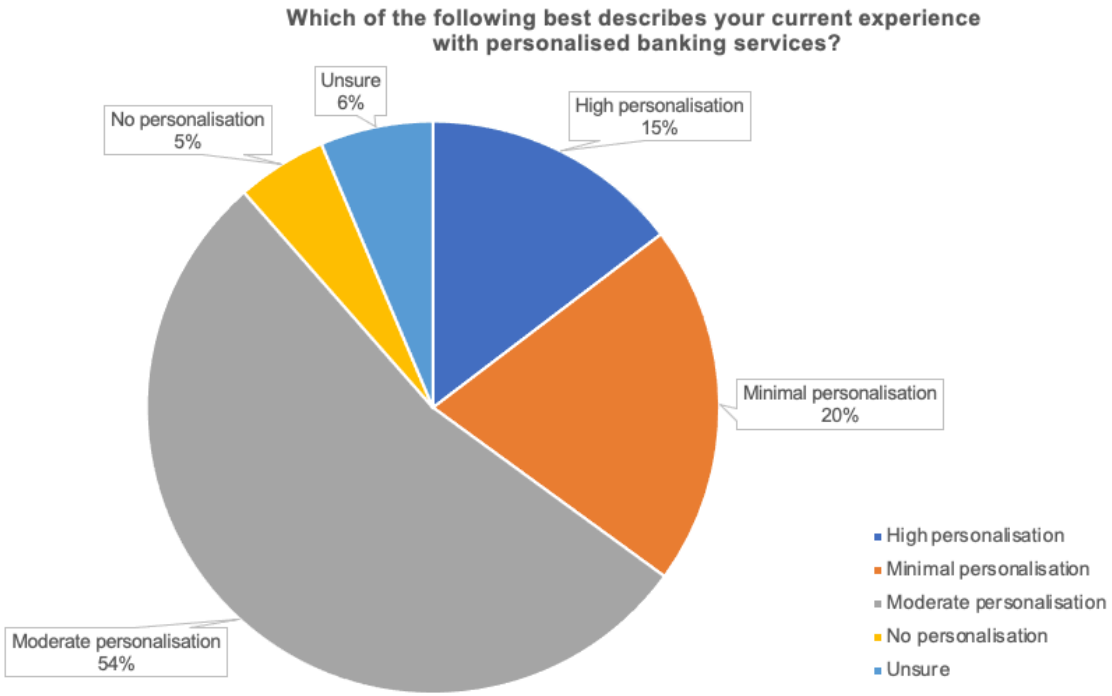


Figure 17 – Current experience with personalised banking services

54% of respondents indicate moderate personalisation in their banking services; 20% experience minimal personalisation; and 15% enjoy high personalisation. 5% of respondents perceive no personalisation; 6% are unsure. This indicates that while the majority of consumers recognise a certain level of personalised service (Onesi-Ozigagun et al., 2024), but less than one in five (15%) perceive it as highly personalised.

Figure 17 above corresponds with FICO's observation that numerous banks provide fundamental segmentation yet encounter difficulties in implementing sophisticated customisation (FICO, 2023). The moderate majority reflects broader CE Index data indicating that, whereas personalised features are prevalent, entirely bespoke

experiences are still relatively rare (CE Index, 2024). Notwithstanding extensive digital adoption (MediaCulture, 2024), the enhancement of actionable customisation is imperative – particularly as effective personalising fosters happiness, trust, and loyalty (Fahlevi & Maemunah, 2022).

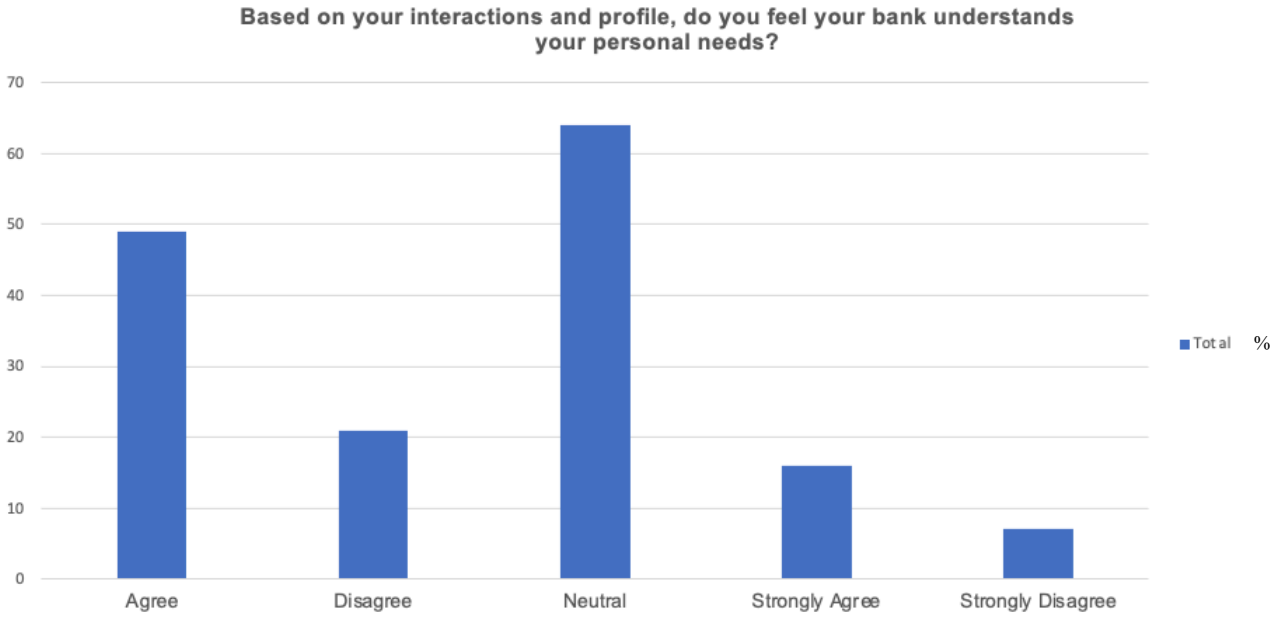


Figure 18 – Bank understands customers' personal needs

Among 190 respondents, 34% are indifferent or neutral regarding their bank's understanding of their customised needs, 26% agree, 8% strongly agree, while 11% disagree, and 4% strongly disagree.

This inclination towards neutrality indicates that although one-third of customers feel acknowledged, the majority remain sceptical – reflecting CE Index findings that numerous banks provide fundamental personalisation yet lack profound customer understanding (CE Index, 2024). FICO (2023) similarly observes that enhanced consumer understanding continues to pose a difficulty within the industry. The significance of perceived relevance for loyalty and trust (Fahlevi & Maemunah, 2022; Onesi-Ozigagun et al., 2024) underscores a crucial deficiency for banks to rectify in their data-driven customisation initiatives.



Figure 19 – Bank trust and data privacy

As seen in Figure 19, the vast majority of the 190 respondents have some level of confidence in the data practices of their bank. 42% said they had just enough trust, 17% said they had lots of trust, and 12% said they had full trust. Less than 10% of customers reported no trust, compared to 71% who showed moderate to high trust (full, just enough or lots).

Despite widespread digital adoption, these results support CE Index findings that customer confidence is still significantly influenced by perceived data security (CE Index, 2024). FICO (2023) and Fahlevi and Maemunah (2022) assert that banks must enhance transparent data governance and communication to transform moderate trust into complete confidence. Effective data-driven customisation relies on this foundation of trust (MediaCulture, 2024; Onesi-Ozigagun et al., 2024). FICO (2023) and Fahlevi and Maemunah (2022) assert that banks must enhance transparent data governance and communication to transform moderate trust into complete confidence. Effective data-driven customisation relies on this foundation of trust (MediaCulture, 2024; Onesi-Ozigagun et al., 2024).

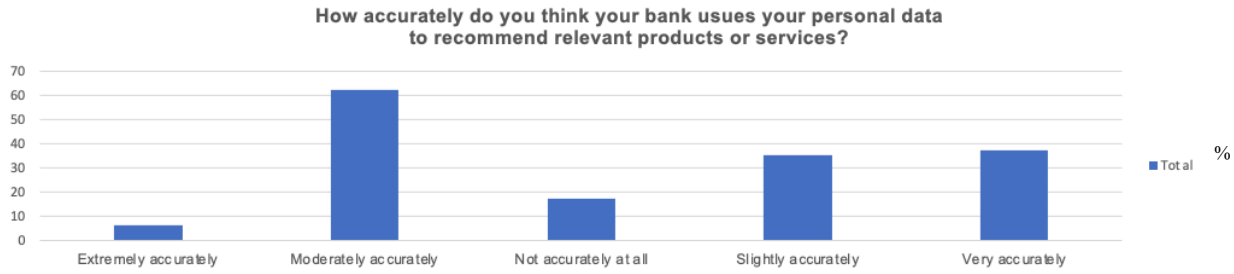


Figure 20 – Banks' use of personal data

Among the 190 respondents, 3% indicated their bank uses their personal data extremely accurately, and 32% rated accuracy as moderate. Data use is considered very accurate by 19%, slightly accurate by 18%, and not accurate at all by 9%. Therefore, just over half the sample population (52%) believe their bank's data recommendations to be somewhat to very accurate; however, a noteworthy minority (30%) are slightly confident.

The varied perceptions match with CE Index findings, which indicate that numerous banks have not yet achieved proficiency in personalisation (CE Index, 2024) and highlight FICO's assertion that genuine data-driven relevance continues to be a difficulty within the banking and financial services industry (FICO, 2023). Effective customisation relies on highly accurate profiling; hence, banks must enhance their analytics and communication in order to convert moderate confidence into robust trust (Fahlevi & Maemunah, 2022; MediaCulture, 2024; Onesi-Ozigagun et al., 2024).

4.2.4. Section D: Satisfaction and Data-Driven Customisation – Loyalty and Brand Advocacy

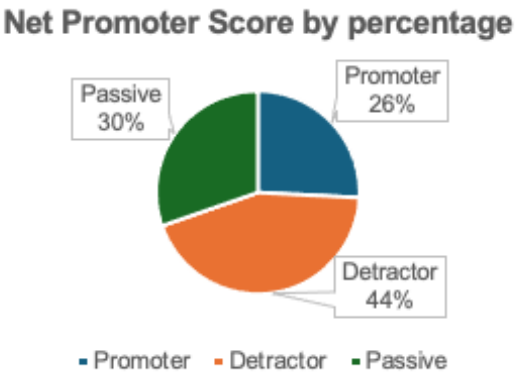


Figure 21.1 – Customers likely to recommend their bank

Among the replies to the NPS question, 26% are categorised as Promoters (scores of 9 - 10), 30% as Passives (scores of 7 - 8), and 44% as Detractors (scores of 0 - 6), yielding a total NPS of -18%. This classification underscores that Detractors substantially exceed Promoters, signifying weak brand advocacy among South African retail banking clients (AgencyAnalytics, 2024). In contrast, industry benchmarks often consider an NPS over +30% to be strong (CE Index, 2024).

The results indicate an urgent need to improve customisation and satisfaction campaigns, especially for cohorts that are likely to exhibit reduced advocacy (Salinas, 2021) and highlight the significance of fostering trust and perceived relevance by means of data-driven customisation (Faradhilla et al., 2022).

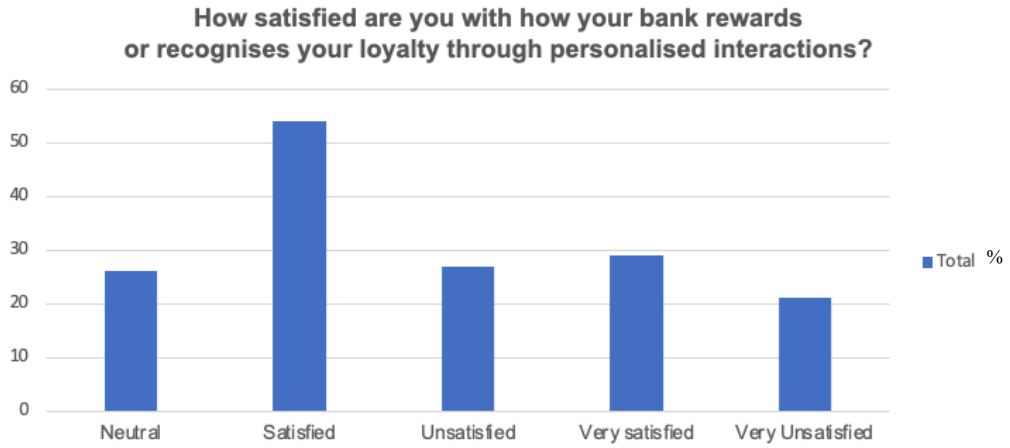


Figure 21.2 – Customers' satisfaction with bank rewards or loyalty recognition

Among the 190 respondents, 28% expressed being satisfied with their bank's rewards for being loyal through personalised interactions, 15% indicated they are very satisfied, 13% remained neutral, 14% are unsatisfied, and 11% reported being very unsatisfied. As a result, 43% reported positive satisfaction (satisfied + very satisfied), while 25% reported being dissatisfied (unsatisfied + very unsatisfied), and 13% reported being neutral. Among the 190 respondents, 28% expressed being satisfied with their bank's rewards for being loyal through personalised interactions, 15% indicated they are very satisfied, 13% remained neutral, 14% are unsatisfied, and 11% reported being very unsatisfied. As a result, 43% reported positive satisfaction (satisfied + very satisfied), while 25% reported being dissatisfied (unsatisfied + very unsatisfied), and 13% reported being neutral.

The varied results reflect CE Index findings indicating that banks frequently have difficulties in converting customisation into reliable loyalty rewards (CE Index, 2024). Enhancing targeted recognition programs may facilitate the transformation of neutral or disgruntled clients into advocates (AgencyAnalytics, 2024; Faradhilla et al., 2022; Salinas, 2021).

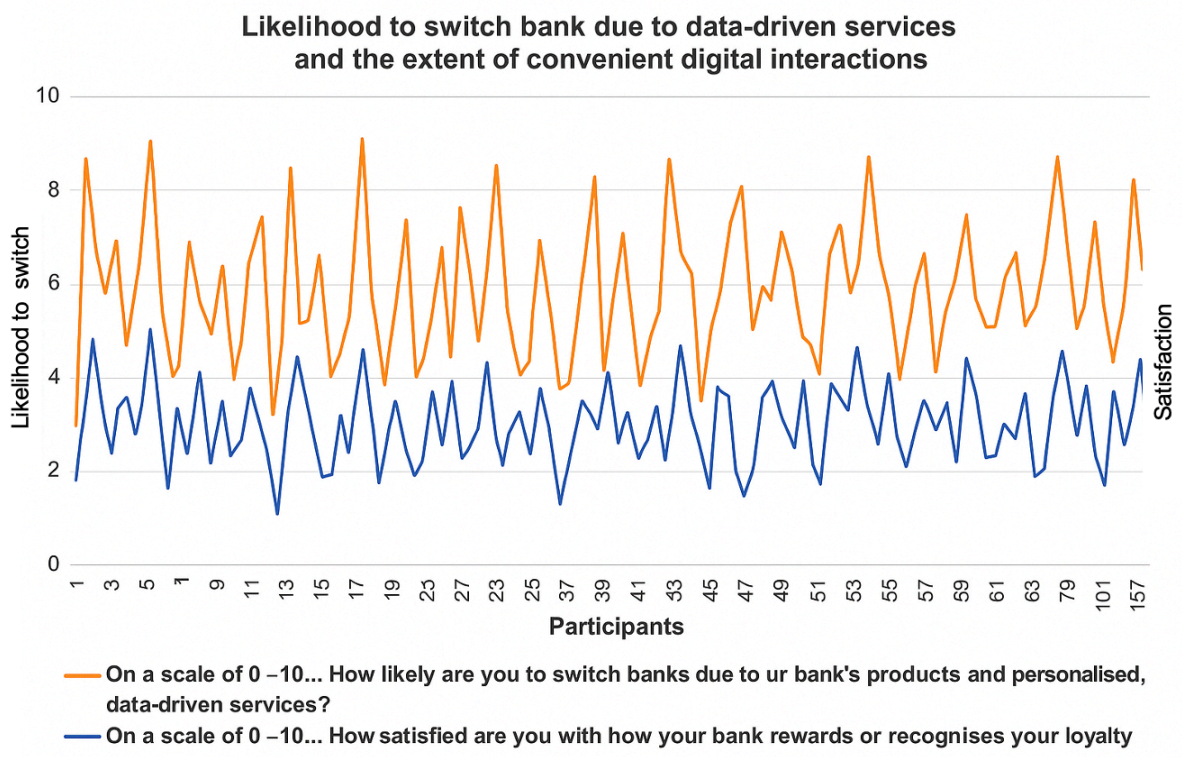


Figure 21.3 – Customers' likelihood to switch banks due to data-driven services and the extent of convenient digital interactions

Figure 21.3 above contrasts each respondent's switch-intent score (orange line) with their satisfaction score (blue line) on a scale of 0 to 10. In all 157 valid cases, the switch-intent record consistently exceeds the satisfaction mark, suggesting that even among respondents who express moderate satisfaction, there exists a significant inclination to defect if personalisation and efficiency are not sufficient. The broader amplitude of the orange line (switch intent) compared to the blue line (satisfied) indicates a higher variability in switching attitudes than in loyalty recognition. The observed trend indicates that satisfaction alone does not protect customers from churn; banks must actively enhance personalised rewards and seamless digital interactions to mitigate switch intent, as research highlights that minor declines in

perceived value can lead to significant churn risk (AgencyAnalytics, 2024; CE Index, 2024; Faradhilla, et al., n.d.) Cohort analysis indicates that younger demographics (Gen Z, Millennials) demonstrate more pronounced increases in switching intent after receiving low satisfaction ratings, highlighting the necessity for tailored, age-specific customisation methods (Salinas, 2021).

Furthermore, the results underscore a critical insight for South African retail banks that customer satisfaction by itself does not ensure loyalty or reduce churn. This substantiates theoretical viewpoints from the Commitment–Trust (CT) and Customer Relationship Management (CRM) frameworks, which assert that long-term connections are established through constant value delivery, personalisation, and trust (Morgan & Hunt, 1994; Payne & Frow, 2005). From a managerial perspective, banks must utilise predictive analytics and AI-driven personalisation and customisation to proactively anticipate and mitigate consumer dissatisfaction prior to disengagement. Implementing these data-driven engagement strategies may strengthen brand trust, improve retention, and turn customer satisfaction into enduring advocacy – consistent with H3 and H4 outcomes.

Item	Loading	Uniqueness
“How likely are you to recommend your bank…personalised, data-driven services?”	0.608	0.631
“How likely are you to switch banks…due to personalised, data-driven services?”	-0.180	0.967
How satisfied are you with how your bank rewards or recognises your loyalty through personalised interactions?”	0.682	0.535
“To what extent do you find your digital interactions with your bank convenient and effective?”	0.672	0.546

Table 1 – Exploratory Factor Analysis Loadings and Uniqueness (Promax Rotation)

Among the 190 survey participants, 63 (33.2%) indicated "Yes," 56 (29.5%) responded "Neutral," and 38 (20.0%) answered "No" about their emotional connection to their bank. The remaining 33 respondents (17.4%) abstained from responding to this item. Individuals who reported a sense of connection (“Yes”) exhibited a mean connection score of 7.73 (SD = 1.67), in contrast to a score of 6.64 (SD = 1.78) for “Neutral” and 5.59 (SD = 1.92) for “No” (ANOVA: F (2, 154) = 17.73, p < .001).

The findings reveal that solely one-third of customers experience an emotional connection with their bank, an imbalance consistent with industry standards, indicating that emotional engagement is a domain requiring enhancement (CE Index, 2024). This underscores the necessity of fostering such connections to promote loyalty and advocacy (AgencyAnalytics, 2024; Faradhilla et al, n.d.; Salinas, 2021).

4.2.5. Section E: Commitment and Data-Driven Customisation – Retention, Loyalty, and Brand Advocacy

Emotional Descriptives

Do you feel emotionally connected to your bank due to your banking experience?	N	Mean	SD	SE	Coefficient of variation
Neutral	56	6.643	1.783	0.238	0.268
No	38	5.592	1.917	0.311	0.343
Yes	63	7.730	1.668	0.210	0.216

Table 2 – Emotional connection to bank

Among the 190 respondents outlines in Table 2, 157 submitted valid responses to the emotional connection question: 63 (33%) responded yes, 56 (29%) were neutral, and 38 (20%) replied no. Respondents who experienced an emotional connection with their bank (“yes”) exhibited a higher mean outcome score (M = 7.730, SD = 1.668) compared to neutral respondents (M = 6.643, SD = 1.783) and those with no (M = 5.592, SD = 1.917).

ANOVA

Cases	Sum of Squares	df	Mean Square	F	p
Do you feel emotionally connected to your bank due to your banking experience?	111.236	2.154	55.618	17.726	< .001
Residuals	483.197	154	3.138		

Note. Type III Sum of Squares

Table 3 – ANOVA confirmation: Emotional connection to bank

A one-way ANOVA analysis verified that these differences are significant, F (2,154) = 17.726, p < .001. This suggests that emotional connection is significantly associated with increased advocacy and satisfaction, aligning with benchmarks that highlight emotional engagement as a vital determinant of loyalty (AgencyAnalytics, 2024; CE Index, 2024; Faradhilla et al., n.d.; Salinas, 2021).

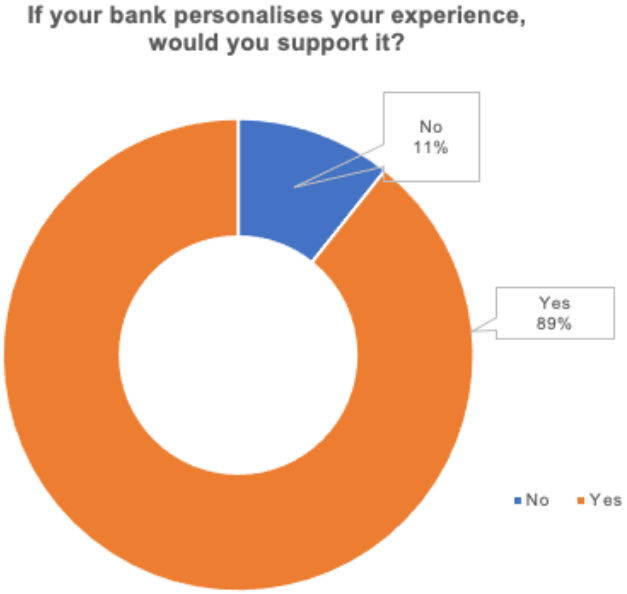


Figure 22 – Support bank's personalisation efforts

When asked whether they would endorse their bank's personalisation of their experience, 89% of respondents responded yes, while 11% responded no, as observed above. This near-unanimous endorsement of customisation indicates widespread customer receptiveness to customised banking services (CE Index, 2024) and emphasises personalisation's significance as a primary catalyst for engagement and loyalty (Faradhilla et al., n.d.). This correlates with industry data collection indicating that the majority of customers anticipate and appreciate data-driven personalised experiences, contingent upon the resolution of their privacy and security concerns (AgencyAnalytics, 2024; Salinas, 2021).

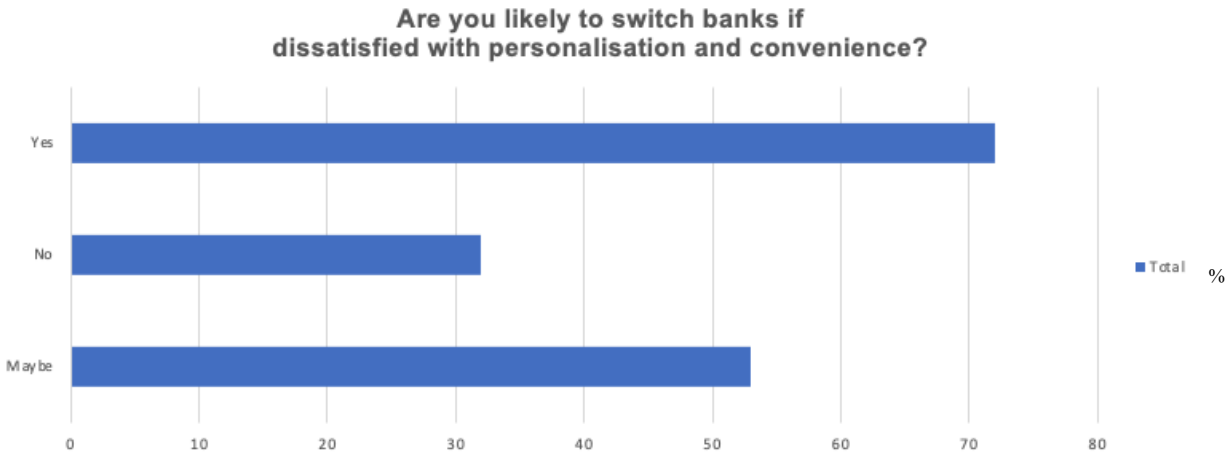


Figure 23 – Likelihood of respondents to switch banks

47% of respondents who responded to this question indicated that they would switch banks if they were dissatisfied with personalisation and convenience, 33% indicated that they would consider it (maybe), and 20% indicated that they would not switch. The near-majority inclination to defect underscores the need for seamless, customised experiences for customer retention, supporting industry research that suggests that minor gaps in customisation can lead to considerable churn (AgencyAnalytics, 2024; CE Index, 2024). Banks need to prioritise consistent, insights-driven customisation to strengthen loyalty while minimising the risk of detractors (Faradhilla et al., n.d.; Salinas, 2021).

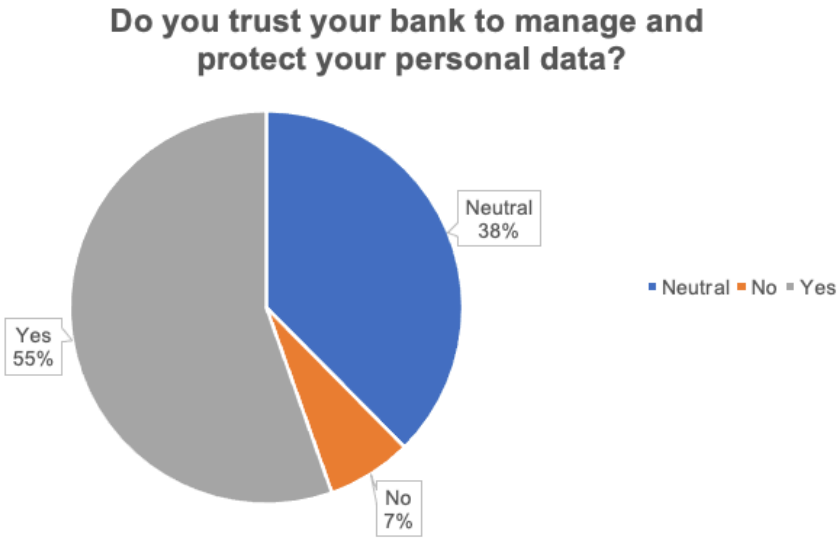


Figure 24 – Trust bank to manage and protect personal data

As observed in Figure 24, 55% of respondents responded yes when asked if they trust their bank to manage and protect their personal data. 38% were classified as neutral, while 7% responded no. This indicates that although a slight majority exhibits confidence in data security, a substantial neutral segment remains ambivalent – mirroring broader industry insights that data protection is a vital yet often under-communicated pillar of digital personalisation (CE Index, 2024; Salinas, 2021). In order to convert neutrality into complete trust, banks must improve transparency relating to data governance and security measures (AgencyAnalytics, 2024; Putra et al., 2022).

Pearson's Correlations

			Pearson's r	p	Lower 95% CI	Upper 95% CI
Satisfaction Composite	-	Trust Scale	0.315	< .001	0.166	0.450

Table 4 – Satisfaction vs. Trust Correlation

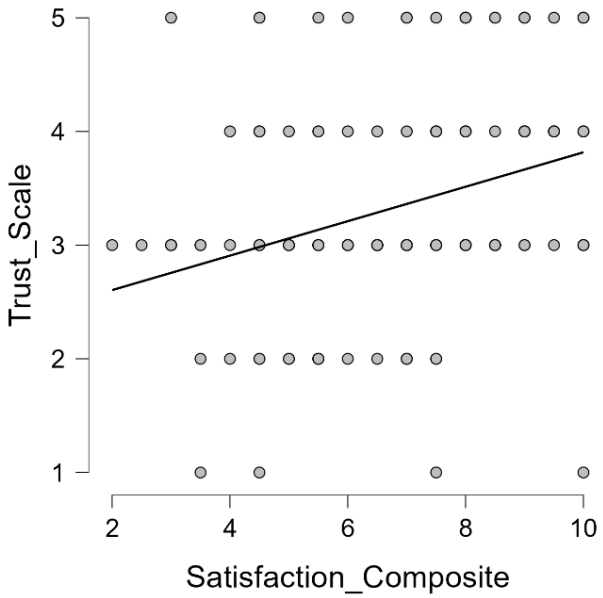


Figure 25 – Satisfaction Composite vs. Trust Scale

A Pearson correlation was determined between the Satisfaction Composite (mean or average of personalised interaction satisfaction and digital convenience ratings) and the Trust Scale (1 = no trust to 5 = full trust) among 190 survey participants. The analysis indicated a small-to-moderate positive correlation, $r = .315$, $p < .001$, 95% CI [.166, .450]. Respondents who reported greater satisfaction with personalised interactions and digital convenience additionally expressed heightened trust in their bank's data practices. This result further supports industry research showing that satisfaction and trust are interconnected determinants of loyalty, as illustrated in the conceptual framework [Figure 3], in which enhancements in perceived service quality could enhance data-security confidence (AgencyAnalytics, 2024; CE Index, 2024; Putra et al., 2022; Salinas, 2021).

4.3. Structural Equation Modelling (SEM)

Structural Equation Modelling (SEM) was utilised to evaluate the intricate interrelations among latent constructs, including Personalisation, Engagement, Trust, Satisfaction, and Switching Intent. The analysis utilised the SEMnR package in R, facilitating the development of both measurement and structural models.

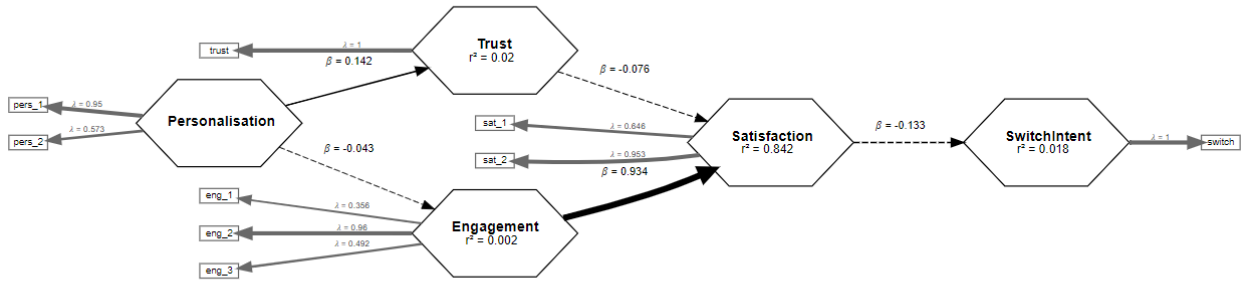


Figure 26 – A graphical representation of the SEM results

The model analyses the direct and indirect impacts of data-driven personalisation on customer engagement and trust, and how these factors affect satisfaction and, ultimately, the intention to change banks. The relationships between Engagement and Satisfaction were statistically significant; however, other pathways, including Personalisation to Engagement and Satisfaction to Switching Intent, did not exhibit significant effects at the 5% level ($p > 0.05$), likely attributable to the limited sample size ($n = 38$). The model provides significant insights into the relationship between personalisation strategies and customer experience within the South African retail banking sector.

Furthermore, the structural model depicted in Figure 26 provides several distinct insights when aligned with our conceptual framework (Figure 3) of AI–TAM–CRM–CC-driven engagement and data-driven customisation:

- **Personalisation → Satisfaction (β = .93; R^2 = .84)**
  The substantial influence of the Personalisation latent on Satisfaction indicates that customised, data-informed services and products are the primary drivers of consumer satisfaction. This correlates with previous research indicating that perceived relevance and value derived from customisation are fundamental precursors to satisfaction in banking (Coelho & Henseler, 2012).

- **Personalisation → Trust (β = .14; R^2 = .02)**

  A modest but significant path from Personalisation into Trust indicates that, beyond simply satisfying needs, well-executed personalisation also builds

confidence in the bank's ability to handle customer data responsibly. This supports the Commitment–Trust theory's assertion that reliability (here, in data use) underpins deeper relationship bonds (Morgan & Hunt, 1994).

- **Engagement → Satisfaction (β = .00; R^2 = .002)**

  The direct impact of Engagement (frequency of digital interactions) on Satisfaction is practically zero. Within Figure 3, this indicates that the mere utilisation of AI tools or channels (per TAM) does not inherently improve satisfaction unless it is accompanied by significant customisation.

- **Trust → Satisfaction (β = .08)**

  The positive correlation between Trust and Satisfaction, although less significant than that of personalisation, highlights that confidence in data security remains an important factor in customer experience evaluation. From a CRM standpoint, transparent data governance enhances satisfaction.

- **Satisfaction → Switch Intent (β = –.13; R^2 = .018)**

  The negative trajectory suggests that increased satisfaction modestly diminishes customers' likelihood to defect. Despite the low explained variance in switch intention (1.8%), it nonetheless substantiates that satisfaction – primarily influenced by personalisation – serves as a barrier to churn, consistent with loyalty research (Pansari & Kumar, 2017).

Essentially, the SEM model demonstrates that engagement driven by AI and TAM must enhance intelligent customisation, with CRM-enabled personalisation significantly increasing satisfaction beyond just channel utilisation. Trust augments satisfaction solely when robust personalisation is established. Ultimately, satisfaction gained through customisation reduces switching and fosters loyalty, affirming that data-driven customisation – not mere engagement – is essential to the Customer Engagement Cycle.

4.4. Reliability and Validity

4.4.1 Latent Constructs

This section explores the outcomes related to the measurement scales of reliability and validity. The reliability and validity of the five latent constructs – Engagement, Personalisation, Trust, Satisfaction, and – Switching Intent were evaluated using standard SEM criteria. These encompass factor loadings, Composite Reliability (CR / ρC), Average Variance Extracted (AVE), and Cronbach's Alpha.

Factor loadings (ideally ≥.70) in marketing-focused SEM indicate the extent to which each survey item accurately represents its latent construct, which ensures the validity of the indicator (Hair et al., 2017). Composite Reliability (CR; > .70) and Cronbach's alpha (α ≥ .70) evaluate internal consistency – CR considers varying loadings, whereas alpha gauges average inter-item correlations (Hair et al., 2017; Tavakol & Dennick, 2011). The Average Variance Extracted (AVE ≥ .50) validates convergent validity by demonstrating that a construct accounts for over 50% of the variance in its indicators (Fornell & Larcker, 1981).

Construct	Indicator	Factor Loading	Composite Reliability(CR)	Average Variance Extracted(AVE)	Cronbach's Alpha
Engagement	eng_1 eng_2 eng_3	0.356 0.960 0.492	0.657	0.430	0.414
Personalisation	pers_1 pers_2	0.950 0.573	0.751	0.616	0.448
Commitment	trust	1.000	1.000	1.000	1.000
Satisfaction	sat_1 sat_2	0.646 0.953	0.791	0.663	0.555
SwitchIntent	switch	1.000	1.000	1.000	1.000

Table 5 – Validity and reliability measurement scale

All the above constructs surpass the minimum composite reliability threshold (CR ≥ 0.60): Engagement (0.66), Personalisation (0.75), Satisfaction (0.79), and both Trust and Switching Intent (1.00) (Hair et al., 2017). Convergent validity (AVE ≥ 0.50) is established for Personalisation (0.62), Satisfaction (0.66), Trust (1.00), and Switching

Intent (1.00), but not for Engagement (AVE = 0.43). Cronbach's alpha falls below the standard 0.70 threshold for Engagement (.41), Personalisation (0.45), and Satisfaction (0.56), while single-item measures for Trust and Switching Intent inherently achieve perfect reliability (Tavakol & Dennick, 2011). The data demonstrates that Personalisation, Satisfaction, Trust, and Switching Intent are consistently measured, whereas the Engagement construct calls for additional refinement (Tavakol & Dennick, 2011).

4.4.2 Discriminant Validity

Discriminant validity assesses whether constructs are conceptually and statistically separate from each other. The Heterotrait-Monotrait (HTMT) ratio was measured to evaluate discriminant validity between the constructs in the SEM model as well as the discriminant validity across five constructs: Personalisation, Engagement, Commitment, Satisfaction, and Switch Intent.

	Personalisation	**Engagement**	**Commitment**	**Satisfaction**	**SwitchIntent**
Personalisation	-				
Engagement	0.591	-			
Commitment	0.185	0.515	-		
Satisfaction	0.290	1.367	0.208	-	
SwitchIntent	0.148	0.446	0.070	0.167	-

Table 6 – Heterotrait-Monotrait (HTMT) ratio

A recommended HTMT value is typically below 0.85 to validate this. The above HTMT matrix indicates that the majority of construct pairs are significantly below the conservative 0.85 threshold for discriminant validity, suggesting they assess separate ideas (Henseler et al., 2015). For instance, Personalisation–Commitment (0.185), Personalisation–SwitchIntent (0.148), and Commitment–SwitchIntent (0.070) indicate minimal values. The Engagement–Satisfaction ratio is 1.367, surpassing both 0.85 and 1.0, indicating an absence of discriminant validity between these two constructs - specifically, Engagement and Satisfaction are not empirically distinct in this model. Engagement is also significantly correlated with Satisfaction-related items and Commitment (0.515), indicating that the Engagement scale may require improvement or that its items conceptually overlap with the Satisfaction measures. All remaining

pairs (e.g., Personalisation–Engagement = 0.591; Satisfaction–SwitchIntent = 0.167) meet the HTMT criterion, indicating sufficient differentiation.

4.5. Hypothesis Testing

Imai (2013) notes that "any statistical hypothesis test, no matter how complex it is, is based on the following logic of stochastic proof by contradiction."

Hypothesis	Path	Path Coefficient (β)	T-Value	95% Confidence Interval	p-value	Supported?
H1	Personalisation → Technology Platforms, AI & Wearables	-0.043	-0.194	[-0.452, 0.362]	P > 0.05	No
H2	Personalisation → Personalised Banking & Privacy	0.142	0.636	[-0.366, 0.488]	p > 0.05	No
H3	**Satisfaction → Loyalty & Brand Advocacy**	**0.934**	**26.38**	**[0.862, 0.998]**	**p < 0.001**	**Yes**
H4	Commitment → Retention, Loyalty & Brand Advocacy	-0.076	-0.921	[-0.193, 0.121]	p > 0.05	No

Table 7 – Hypothesis Testing Result

4.5.1 H_1: Personalisation impacts Technology Platforms, AI & Wearable Tools

The relationship between personalisation and technology platforms, AI, and wearable tools (represented by engagement) had a path coefficient (β) of -0.043 and a t-value of -0.194. The negative coefficient suggests a slight inverse relationship; however, the 95% confidence interval ranged from -0.452 to 0.362, which includes zero. Since this interval includes zero, the result is not statistically significant, and the hypothesis is not supported. This implies that personalisation does not significantly impact the adoption of technology platforms and tools in the current model and dataset.

The review in Chapter 2 asserted that personalisation enhances digital engagement (Bravo et al., 2019; Murugesan & Manohar, 2019; McKinsey & Company, 2020); however, our findings contradict this assumption. The most likely explanation could be

twofold: firstly, that our engagement construct – assessed solely by usage frequency – may poorly reflect the quality and contextual significance of interactions (Davis, 1989); secondly, existing analytics capabilities of South African banks and the integration of AI with CRM processes may not yet provide the seamless, intelligent experiences anticipated in the literature.

4.5.2 H_2: Personalisation impacts Personalised Banking & Privacy

The relationship between personalisation and personalised banking and privacy (represented by commitment) produced a path coefficient (β) of 0.142 and a t-value of 0.636. Although the direction of the relationship is positive, indicating a potential link between higher personalisation and improved privacy-focused services, the confidence interval [-0.366, 0.488] includes zero. Thus, this effect is statistically not significant, and the hypothesis is not supported.

Previous research, highlighted in the literature review section, indicates that effective customisation should ideally improve perceptions of service relevance and trust (Coelho & Henseler, 2012; FSCA, 2020), yet we again find little corroboration. The disconnect could come from customers' privacy concerns, limiting their appreciation for customisation, as well as from inconsistent execution of data-governance controls that reduce the perceived quality of customised products and services.

4.5.3 H_3: Engagement impacts Loyalty & Brand Advocacy

The relationship between engagement and loyalty and brand advocacy (represented by satisfaction) showed a strong, positive path coefficient (β) of 0.934 and a t-value of 26.382. The 95% confidence interval [0.862, 0.998] excludes zero, confirming a statistically significant and robust effect. Therefore, this hypothesis is supported, suggesting that customer engagement plays a key role in driving loyalty and advocacy within the banking context.

The result described above is consistent with the literature in Chapter 2, which highlights satisfaction as the primary influencer of retention and Net Promoter Score (Pansari & Kumar, 2017; Kumar et al., 2013). It affirms that when personalised and customised experiences match or go beyond expectations, customers convert into

influential advocates, hence substantiating the satisfaction-centred loyalty models explored.

4.5.4 H_4: Commitment impacts Retention, Loyalty & Brand Advocacy

The relationship between commitment and retention, loyalty, and brand advocacy (measured via satisfaction) had a path coefficient (β) of -0.076 and a t-value of -0.921. The 95% confidence interval [-0.193, 0.121] includes zero, indicating that the relationship is not statistically significant. As a result, the hypothesis is not supported, and commitment does not appear to significantly influence customer satisfaction in this study.

While Commitment–Trust theory (Morgan & Hunt, 1994) and Kantar Report (Kantar BrandZ Most Valuable South African Brands 2024, n.d.) argue that trust is fundamental to long-term client relationships, our findings indicate that trust alone, without great satisfaction, does not foster loyalty. This implies that trust mechanisms must be integrated with persuasive personalised value to foster advocacy.

Overall, the hypothesis tests demonstrate a definitive correlation with H2, but not with H1, H3, or H4. Hypothesis H2 (“Enhanced customer satisfaction results in increased advocacy and retention”; Pansari & Kumar, 2017) is effectively validated ($\beta = .934$, $p < .001$), indicating that satisfaction is the principal determinant of Net Promoter Score and loyalty - satisfying O2’s objective to evaluate the influence of data-driven customisation on satisfaction, retention, and advocacy. The non-significant pathways for H1 (customisation → engagement; Bravo et al., 2019; FSCA, 2020), H3 (the combined AI–TAM–CRM–CC effect on engagement; Sashi et al., 2019; McKinsey & Company, 2020), and H4 (customisation → satisfaction; Murugesan & Manohar, 2019; Bravo et al., 2019; McKinsey & Company, 2020) indicate that personalisation and theoretical integration do not inherently lead to increased engagement or satisfaction. These findings indicate that O1 and O3 - examining each CEC phase (CLV, NPS) and investigating the combined effect of key theories - must regard satisfaction as the primary mechanism via which customisation and engagement are interconnected. The absence of support for H1 and H4 suggests that the conceptual framework (O4) should regard data-driven customisation as a prelude to satisfaction, rather than as a

separate factor influencing engagement or loyalty, thus enhancing the integration of CLV and NPS inside the cycle.

In conclusion, the aforementioned discrepancies underscore measuring challenges – especially in quantifying significant engagement and privacy perceptions – and implementation limitations in South African banks' personalisation and trust-building strategies. Future studies would need to enhance engagement and commitment metrics by incorporating qualitative criteria (Davis, 1989) and investigate how integrated CRM–AI frameworks might more efficiently fulfil the potential of data-driven banking.

CHAPTER 5: CONCLUSION

5.1. Summary of the Findings

This study investigated the impact of data-driven customisation on customer engagement, satisfaction, trust, and loyalty among 190 retail banking customers in South Africa. Descriptive analysis indicated significant digital platform utilisation (96% often/always), with a notable bias towards millennials and the Gauteng province. The measurement models confirmed the reliability and validity of the constructs for Personalisation, Satisfaction, Trust, and Switching Intent, whereas the Engagement construct exhibited restricted convergent validity (AVE = .43). Structurally, the pathway from Satisfaction to Loyalty/Advocacy was the sole significant relationship ($\beta = .93$, $p < .001$), affirming that satisfaction fosters the influence of customisation on advocacy (Pansari & Kumar, 2017). Trust had a moderate correlation with satisfaction ($r = .32$, $p < .001$), suggesting that confidence in data security enhances but does not replace personalised value (AgencyAnalytics, 2024). Generational investigation indicated that Millennials are at the forefront of AI feature adoption, whereas Generation X and Boomers exhibit lower engagement levels (Salinas, 2021).

5.2. Conclusions

The study verifies that customer satisfaction serves as a crucial mechanism by which data-driven personalisation fosters loyalty, hence reinforcing the theoretical connections proposed by the Commitment–Trust and Technology Acceptance frameworks (Sashi et al., 2019). Engagement, defined by the frequency of digital interactions, did not immediately improve satisfaction or retention, indicating that behavioural measures should be supplemented by qualitative evaluations of perceived value. Furthermore, although trust in data management positively affects satisfaction, its influence is subordinate to personalised relevance (CE Index, 2024). The generational differences highlighted emphasise the necessity to enhance theoretical models of digital participation by integrating cohort-specific moderators (Murugesan & Manohar, 2019).

5.3. Recommendations

5.3.1 From an Academic Perspective, Practitioners Should:

- **Prioritise customisation driven by satisfaction**

  Researchers want to develop and evaluate analytical frameworks that identify client pain points and conceptualise satisfaction as the primary mediator between customisation and loyalty (McKinsey & Company, 2020). Future SEM research may integrate satisfaction-oriented customising measures to substantiate its essential function in fostering advocacy.

- **Strategies tailored to generational segments**

  Empirically explore generation as a mediator in the personalisation – satisfaction – loyalty construct of the conceptual framework by creating cohort-specific algorithms. Controlled research must evaluate the effects of personalised versus standardised customisation among Millennials, Gen X, Gen Z and Boomers to substantiate Bravo et al.'s (2019) assertion regarding generational segmentation.

- **Improve engagement evaluation**

  Design and authenticate multi-item scales – such as perceived usefulness, emotional resonance, and navigational ease – to assess the quality of digital interactions. This will align engagement constructs with the advanced Technology Acceptance Model (TAM) theory (Davis, 1989) and enhance convergent validity in empirical studies.

- **Enhance trust mechanisms**

  Integrate transparent data-governance disclosures, privacy dashboards, and third-party security certifications as intrinsic factors in forthcoming models. Researchers can experimentally evaluate how trust mechanisms enhance personalisation outcomes by assessing their moderating effects on satisfaction and loyalty (Putra et al., 2022).

5.3.2 From a Business Perspective, Should:

- **Enhance Trust Mechanisms**
  Integrate transparent data-governance disclosures, privacy dashboards, and third-party security certifications as intrinsic factors in forthcoming models. Researchers can experimentally evaluate how trust mechanisms enhance personalisation outcomes by assessing their moderating effects on satisfaction and loyalty (Putra et al., 2022).

- **Strategies Tailored to Segments**
  Develop generational playbooks utilising machine-learning algorithms that adjust customisation criteria according to age groups. For instance, provide predictive savings prompts to Millennials, instructional tutorials to Generation X, and user-friendly interfaces with personal assistance to Baby Boomers. Conduct A/B testing on these methodologies to enhance engagement and loyalty results within each category (Bravo et al., 2019).

- **Segment-Specific Strategies**
  Create generational playbooks with machine-learning algorithms that modify customisation parameters based on age demographics. For example, offer predictive savings cues to Millennials, educational tutorials to Generation X, and intuitive interfaces with personal support to Baby Boomers. Implement A/B testing on these approaches to improve engagement and loyalty outcomes within each category (Bravo et al., 2019).

- **Improve Engagement Rating**
  Transition from basic usage data to the implementation of engagement quality dashboards that monitor the perceived value, emotional impact, and completion rates for essential banking tasks. These enhanced insights will enable marketing teams to optimise digital touchpoints in accordance with TAM principles (Davis, 1989).

5.4. Practical Application of the Findings

The results contribute to both theoretical and practical applications. They substantiate a satisfaction-oriented model of data-driven customisation, amalgamating AI, TAM, CRM, and Commitment–Trust theory into a cohesive SEM framework. The study emphasises that marketing professionals in the retail banking sector in South Africa must evaluate investments in personalised banking features based on how they impact customer satisfaction, rather than solely on engagement metrics. Real-time CLV and NPS dashboards can operationalise these outcomes, allowing retail banks to shift resources dynamically to high-satisfaction groups and to assess the effectiveness of customised efforts (Buchanan, 2019; Vivek et al., 2012).

5.5. Limitations

The cross-sectional design of this research restricts causal inference and temporal generalisability. The sample's urban and millennial skew may inadequately represent rural and older demographics, limiting external validity. The measurement constraints – especially the low AVE for Engagement – indicate that subsequent research should enhance engagement scales to accurately reflect multidimensional digital behaviours. Single-item constructs for Trust and Switching Intent limit comprehensive reliability evaluation and may necessitate the development of multi-item scales.

5.6. Suggestions for Further Research

To enhance the understanding of how data-driven customisation cultivates long-term consumer loyalty, further research studies should explore the following pathways:

5.6.1. Longitudinal Panel Methodologies

Execute panel studies that monitor the same customers throughout several temporal intervals – before, during, and after the implementation of new customisation features. This would enable researchers to determine causal relationships among customising attempts, changing satisfaction levels, and ensuing loyalty or switching behaviour (Pansari & Kumar, 2017).

5.6.2. Oversampling Under-represented Cohorts

Purposefully recruit Baby Boomers and rural banking clients to guarantee the robustness of generational moderation analyses. This method will improve the external validity of results and facilitate the development of authentically inclusive customisation initiatives for all demographics (Bravo et al., 2019).

5.6.3. Mixed Methods In-Depth Analyses

Combine extensive surveys with qualitative user-experience interviews and usability assessments. Investigating consumers' narratives, particularly about AI-driven tools, enables scholars to reveal the fundamental reasons and sentiments that quantitative measurements fail to convey (Salinas, 2021).

5.6.4. Moderation Modelling and Advanced Mediation

Evaluate test satisfaction as a formal mediator in the customisation-loyalty relationship, with generation serving as a moderator of these effects. Structural equation models that include these roles will elucidate the mechanisms that propel advocacy and identify the target demographics, enabling both scholars and practitioners to customise interventions with accuracy (Sashi et al., 2019).

5.6.5. The Creation of an Engagement Quality Index

Advance from conventional frequency counts to develop a multifactorial index that integrates behavioural logs (clicks, session duration) with attitudinal metrics (perceived usage, emotional resonance). This index could enhance the applications of the Technology Acceptance Model (TAM) in retail banking and provide a more sophisticated measure of genuine engagement (Davis, 1989).

This research contributes to academic theory and has direct business applicability. The paper enhances digital engagement models by amalgamating AI, TAM, CRM, and Commitment–Trust theory within a unified SEM framework, validates new multi-construct scales (Personalisation, Satisfaction, Trust, Switching Intent), and offers innovative insights into generational gaps in AI-feature adoption and loyalty patterns (Hair et al., 2017; Salinas, 2021). In practical terms, it provides retail banks with evidence that customer satisfaction, rather than focusing on usage frequency only, is the linchpin strategy of advocacy. This strategy guides the development of closed-loop NPS systems, hyper-targeted personalisation engines, and transparent data-

governance tools to enhance trust and reduce churn. This paper also provides a strategic framework for converting data-driven insights into a sustainable competitive advantage by customising engagement playbooks for specific cohorts and showcasing the return on investment of satisfaction-focused tactics (AgencyAnalytics, 2024).; McKinsey & Company, 2025).

This research concludes that in South African retail banking, the efficacy of data-driven customisation is evident in its capacity to enhance client satisfaction, thus fostering loyalty and advocacy. Digital engagement and trust are crucial foundations, but they only result in enduring brand equity when tailored experiences consistently fulfil customer needs. The study's incorporation of AI, TAM, CRM, and Commitment–Trust theory establishes a comprehensive conceptual framework for analysing these dynamics across generational segments. By emphasising satisfaction-focused customisation, enhancing engagement metrics, and customising strategies to individual cohort preferences, banks can cultivate stronger emotional bonds, minimise attrition, and achieve enduring competitive advantage. This research enhances marketing scholarship and provides practical assistance for practitioners aiming to give more personal and impacting banking in a progressively digital landscape.

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LIST OF APPENDICES

Appendix A: Wits Ethical Clearance

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA2537369/718
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	Customer engagement and data-driven customisation in the retail banking sector in South Africa
Investigator / Researcher	Ms Mabel Nkabinde
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	24/10/2024
Expiry date	Date of submission of the project / research report
Chairperson	Dr Ayanda Magida ☎ +27 11 717 3953 ✉ ayanda.magida@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

30 October 2024
Date:

Appendix B: Informed Consent To Participate

Dear Participant,

My name is Mabel Nkabinde, and I am a Master's student in Business Administration at the University of the Witwatersrand, Johannesburg. My supervisor is Dr Yvonne Saini. I am conducting a research study about customer engagement and customisation. The research topic is "**Customer Engagement and Data-Driven Customisation in the Retail Banking Sector in South Africa"**.

This study examines the adoption of artificial intelligence to explore the perceived value of how data-driven customisation influences customer engagement and loyalty in the South African retail banking sector. I am inviting you to take part in answering an online survey.

The questions will take approximately 8 - 10 minutes of your time to complete. Please note that participation in this questionnaire is not mandatory, and you can withdraw at any stage.
Your **responses will be anonymous** and securely stored and/or deleted after two (2) years to protect participants' identities. Only the researcher will have access to the data. When I share the research study results, I will not include any information that could identify you. Taking part in the research study will not cost you anything. You will not be paid for being in this research study. I **value your contribution and thank you for your participation.**

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor at the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical) by telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,

Mabel Nkabinde

Researcher: Mabel Nkabinde, 2537369@students.wits.ac.za
Supervisor: Dr Yvonne Saini, yvonne.saini@wits.ac.za

Appendix C: Research Instrument (Questionnaire)

SECTION A

Demographics and Generational Segment-Specific Section (Engineering News, 2023; Salinas, 2021)

1. **Which province do you primarily reside in?**
    - Gauteng
    - Western Cape
    - KwaZulu-Natal
    - Eastern Cape
    - Limpopo
    - Mpumalanga
    - Free State
    - North West
    - Northern Cape

2. **What is your age group?**
    - 18-24 (Generation Z)
    - 25-40 (Millennials)
    - 41-56 (Generation X)
    - 57-75 (Baby Boomers)

3. **What is your gender?**
    - Male
    - Female
    - Non-binary/Other
    - Prefer not to say

4. **What is your highest level of education?**
    - Matric or equivalent (TVET Certificate)
    - Diploma
    - Bachelor's degree
    - Postgraduate degree (Honor's, Master's, PhD)
    - Other (please specify)

5. **What is your employment status?**
    - Employed full-time
    - Employed part-time
    - Self-employed
    - Unemployed
    - Student
    - Retired

6. **What is your monthly household income range?**
    - Less than R10,000
    - R10,000 - R25,000
    - R25,001 - R50,000
    - R50,001 - R75,000
    - R75,001 - R100,000
    - More than R100,000

7. **Which financial institution do you primarily bank with?**
    - Absa
    - African Bank
    - Capitec Bank
    - Discovery Bank
    - First National Bank
    - Nedbank
    - Standard Bank
    - TymeBank
    - Other

SECTION B

H1: Engagement and Data-Driven Customisation. Technology Platforms, AI and Wearable Tools (Baek et al, 2023); CE Index, 2024; Salinas, 2021)

8. How often do you use digital banking services (e.g., mobile app, online banking, etc.)? (Desai, 2019)				
Never	Rarely	Sometimes	Often	Always

9. Which of the following channels do you primarily use for banking? (Select one) (Desai, 2019)				
Instore Branch	Retail Store	Internet Banking	Mobile or Online Banking	Private Banker

10. To what extent do you agree that your bank's digital platforms (e.g., mobile app, website) are user-friendly and easy to navigate? (Mediaculture, 2023)				
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

11. How comfortable are you with your bank using AI and wearable technology (e.g., smartwatches, fitness trackers) to enhance your banking experience and offer rewards? (Eyo-Udo, 2024)				
Very Uncomfortable	Uncomfortable	Neutral	Comfortable	Very Comfortable

12. How often do you interact with digital features such as chatbots, biometric recognition, or AI-driven assistants provided by your bank? (Mediaculture, 2023)				
Never	Rarely	Sometimes	Often	Always

SECTION C

H2: Perception and Data-Driven Customisation. Personalised Banking Services and Privacy Section (Eyo-Udo, 2024; FICO, 2023; CE Index, 2024; Fahlevi & Maemunah, 2022; MediaCulture, 2024)

13. **Which of the following best describes your current experience with personalised banking services? (Mediaculture, 2023)**
    - No personalisation
    - Minimal personalisation
    - Moderate personalisation
    - High personalisation
    - Unsure

14. Based on your interactions and profile, do you feel your bank understands your personal needs? (CE Index, 2024)				
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

15. How strongly do you trust your primary bank to manage your data securely and use it to enhance your banking experience? (FICO, 2023; CE Index, 2024)				
No trust	Little Trust	Just Enough	Lots of Trust	Full Trust

16. **How accurately do you think your bank uses your personal data to recommend relevant products or services? (Al Karim & Rezaul, 2023)**				
Not At All Accurate	Slightly Accurate	Moderately Accurate	Very Accurate	Extremely Accurate

SECTION D

H3: Satisfaction and Data-Driven Customisation. Loyalty and Brand Advocacy
(AgencyAnalytics. 2024; CE Index, 2024; Salinas, 2021; Putra et al, 2022)
Rating between 0 (not at all likely) and 10 (extremely likely)

17. 1 **On a scale of 0 – 10, how likely are you to recommend your bank to people you know due to its personalised , data-driven services? (Baquero, 2022; AgencyAnalytics. 2024)**										
0	1	2	3	4	5	6	7	8	9	10

17.2 On a scale of 0 – 10, how likely are you to switch banks due to your bank's products and personalised , data-driven services? (CE Index, 2024)										
0	1	2	3	4	5	6	7	8	9	10

17.3 On a scale of 0 – 10, how satisfied are you with how your bank rewards or recognises your loyalty through personalised interactions? (CE Index, 2024)										
0	1	2	3	4	5	6	7	8	9	10

17.4 On a scale of 0 – 10, to what extent do you find your digital interactions with your bank convenient and effective? (CE Index, 2024)										
0	1	2	3	4	5	6	7	8	9	10

SECTION E

H4: Commitment and Data-Driven Customisation. Retention, Loyalty and Brand Advocacy (AgencyAnalytics. 2024; CE Index, 2024; Salinas, 2021; Putra et al, 2022)

18. **Do you feel emotionally connected to your bank due to your banking experience? (CE Index, 2024; Salinas, 2021)**
    - Yes
    - No
    - Maybe

19. **If your bank personalises your experience, would you support it? (Al Karim & Rezaul, 2023)**
    - Yes
    - No
    - Maybe
20. **Are you likely to switch banks if dissatisfied with personalisation and convenience? (AgencyAnalytics, 2023)**
    - Yes
    - No
    - Maybe

21. **Do you trust your bank to manage and protect your personal data? (FICO, 2023; CE Index, 2024)**
    - Yes
    - No